Phd LA : Annotated Biblio & Table of Contents

**Top**

[**What is learning analytics?**](#_2e8teajfv8gz) **4**

[**T1 Phd Details**](#_3lzvopdas0f3) **5**

[**T2 Research Objectives**](#_yzjysjlzxb11) **5**

[**T3 Research Questions**](#_w8uw8gnlzvmi) **6**

[**T4 Outcomes of Phd**](#_xoz2elrc8xdf) **6**

[**T5 Paper Plan**](#_ul7s01hsvssr) **7**

[**SUMMARY**](#_48rrfraqybll) **7**

[**T06 Techniques**](#_cjlgo9f8f8oc) **7**

[T08 System/ Application/ Tools](#_2vwx4odzt84j) 8

[T09 Area : Activities / Methods Used](#_77i5fgl603gk) 8

[T10 LA : Factors/ Data for Prediction](#_e3mek137pp0b) 9

[T11 LA : Analytical Methods](#_hvnnu11b7rmm) 10

[T13 LA : Gaps/ Future Work/ Suggestions](#_46jywgoc9usr) 10

[T14 LA : xxxxxxxx](#_sirj3jpwkzfc) 11

[T15 LA : xxxxxxxx](#_b2rldc4t1w4d) 11

[**Templates**](#_9cc7mqbv2sed) **12**

[**T16 - Template with Sample Data**](#_nw9xstqvcqau) **12**

[T17 - Blank Table](#_csgi3ll437a9) 13

[T18 - Blank Table](#_75d9h2qdmb23) 13

[T19 - Blank Table](#_6vndtfpq3tof) 13

[T20 - Blank Table](#_emv3lauedg1u) 14

[**Papers**](#_r3g58kpq1cq3) **14**

[Tables : Start from 21](#_7z50n9hlg8ql) 14

[**Learning Analytics (LA)/ Education Data Mining (EDM) / Learning Management System (LMS)**](#_bnoecurvsiqb) **14**

[TP-1 Title : Factors influencing beliefs for adoption of a learning analytics tool: An empirical study.](#_v4kpaxylgbwh) 14

[T12-2 Title : Improving the Student Experience with Learning Analytics in Construction Project Management Courses](#_8pqvnaiclgph) 15

[T13-3 Title : Course Signals at Purdue: Using learning analytics to increase student success](#_lzyaab5ustxm) 19

[T14-4 Title : Educational Data Mining & Students’ Performance Prediction](#_xcby7hutlnjb) 20

[T15-5 Title: Machine Learning Approaches to Predict Learning Outcomes in Massive Open Learning Courses](#_kedfv7gck7v6) 20

[T16-6 Title: Learning Analytics in a Smart Classroom to Improve eEducation](#_ojqs7fj3ojoj) 20

[T17-7 Title: Big Data and analytics in higher education: Opportunities and challenges](#_fvnu8q6o4ja9) 22

[T18-8 - Title:Comparative Analysis of the Effect of Attendance on Academic Performance of Management and Finance Course Students](#_f2gz6u9xyo8c) 22

[T19-9 Title : An analysis of some factors affecting student academic performance in an introductory biochemistry course at the University of the West Indies](#_9itrrki3k94y) 24

[T20-10 Title : An analysis of some factors affecting student academic performance in an introductory biochemistry course at the University of the West Indies](#_xx42ppt8h0ll) 25

[T21-11 Title: Personalized Multi-Regression Models for Predicting Students’ Performance in Course Activities](#_wsd27fabjjpt) 27

[T22-12 Title: Applying Web-Mining Methods for Analysis of Student Behaviour in VLE Courses](#_2asztpfmt7e2) 28

[T23-13 Title: An Educational Data Mining Model for Predicting Student Performance in Programming Course](#_87799xubwgbt) 28

[T24-14 Title: Factorization Models for Forecasting Student Performance](#_wk7crxdag64) 30

[T25-15 Tile : Mining Educational Data to Predict Students Academic Performance using Ensemble Methods](#_dn0urjr2719y) 31

[T26-16 Title : Learning Management System With Prediction Model And Course-content Recommendation Module](#_7iye7oj9nmul) 31

[T27-17 Title : In-Depth Analysis of the Felder-Silverman Learning Style Dimensions](#_647a4efaoih7) 32

[T28-18 Title : Factors affecting students completion : study of online Masters Program](#_dq6ui1vnhud0) 33

[T29-19 Title : EDM & students performance prediction](#_1cn5lqjfrykl) 33

[T30-20 Title : Use of Felder and Silverman learning style model for online course design](#_mnbdaw2o4dp7) 34

[T31-21 Title : Discovering Students use of Learning Resources with EDM](#_8t0afrr3l8bd) 35

[T32-22 Title : Framework for LA in Moodle for assessing Course Outcomes](#_7d5e2f1xvo4j) 35

[T33-23 Title : Predicting Grades](#_lpqgsjnggfbg) 35

[T34-24 Title : EDM & students performance prediction](#_4h1sqxnp5d50) 35

[T35-25 Title: Finding Key Integer Values in Many Features for Learners Academic Performance Prediction](#_6vvavpt0pzj0) 36

[T36-26 Title : Predicting Students performance based on Learning Style byu using ANN](#_ndpzz7rm0y3i) 36

[T37-27 Title : Using Learning Analytics to Predict Students Performance in Moodle LMS : Case of Mbeya University of Science & Technology](#_lccp57jpegsb) 36

[T38-28 Title : Educational DM & Data Analysis for optimal Learning Content Management](#_gza1ydf83p2) 38

[T39-29 Title : EDM & Learning Analysis](#_wlpve4pe7x6o) 39

[T40-30 Title : Review of EDM Techniques & Recommendation model in analysing Student performance](#_xyyhgzu0jd7s) 39

[T41-31 Title : A survey of EDM research](#_4aij1ito165q) 39

[T41-32 Title : A LA approach for student performance assessment](#_cp0zwpo8cclv) 39

[T43-33 Title: A literature review of empirical research on learning analytics in medical education](#_b02sckaz0to6) 40

[T44-34 Title : Using Learning Analytics to Predict (and Improve) Student Success: A Faculty Perspective](#_jtujw05clcdg) 40

[T45-35 Title : Can we Predict Student Learning Performance from LMS Data ? A Classification approach](#_a9m2ccxmffq) 41

[T46-36 Title : Data mining in course management systems: Moodle case study and tutorial](#_9yc5v95lvrqi) 42

[T47-37 Title : xxxxx](#_lywua7x75lkh) 43

[T48-38 Title : Student Engagement Predictions in an e-Learning Systems and their Impact on Student Course Assessment Scores](#_9wwmmgloqceg) 43

[T49-39 Title : xxxxxx](#_7phw0irpd2wc) 43

[T50-40 Title : xxxxxx](#_mr1uy51m4dl6) 43

[T51-41 Title : LA Challenges : Trade-offs, Methodology, Scalability](#_af3kc0t2re5f) 43

[T52-42 Title : Prediction of student academic performance using Moodle Data from a Further Education setting](#_u7s5hrlq40es) 44

[T53-43 Title : Analysing Performance of Students by using DM techniques (LR)](#_4cdrjv1imj4d) 44

[T54-44 Title: Comparing the factors that predict completion & grades among for Credit & open/ MOOC students in online learning](#_jhjajrk20tmw) 44

[T55-45 Title: Comparison of 17 Blended Courses using Moodle LMS](#_f1ukzysxoxzq) 45

[T56-46 Title : Detecting Learning Styles in Learning Management Systems Using Data Mining](#_rslmmid893t6) 46

[T57-47 Title : E-learning : Challenges & Research opportunities using ML & Data Analytics](#_wxaax0xqsern) 47

[T58-48 Title : EDM & data analysis for optimal learning content management](#_44hh2tya06pt) 47

[T59-49 Title : xxxxx](#_loqb48xnm9cz) 48

[T60-50 Title : Intelligence & affect as predictors of Academic Performance among UG students](#_yuku979a92xy) 48

[T61-51 Title : LA in a smart classroom to improve eEducation](#_1urmkqb4bnrf) 48

[T62-52 Title : Machine Learning Based Student Grade Prediction : Case Study](#_pw7dy1j8f94t) 48

[T63-53 Title: ML application in MOOCs : Dropout prediction](#_5evijtydr81m) 49

[T64-54 Title : ML approaches to predict learning outcomes in Massive Open Learning Courses](#_mi65l83t7sjs) 49

[T65-55 Title : Open Student Models of Core Competencies at the Curriculum level : Using LA for Student retention](#_skse6ihvmbif) 49

[T66-56 Title: Personalised Multi-Regression Models for Predicting students performance in Course Activities](#_3byojsqcikg8) 49

[T67-57 Title : Predicting STEMP achievement with LMS data : Prediction modeling and a Test of an Early Warning System](#_uurethbw1jdk) 50

[T68-58 Title : Predicting Students Performance using Advance Learning Analytics](#_bfmeef74g5y0) 50

[T69-59 Title: When LA meets E-Learning](#_ddp1a7n7xlgw) 50

[T70-60 Title : What is LA about ? A Survey of Different Methods used in 2013-15](#_90cmd541o2f7) 51

[T71-61 Title : Potential of LA & Big Data](#_rydijuos16lo) 51

[T72-62 Title : Educational Data Mining: An Application of Data Mining To Estimate Students’ Performance](#_ewq9cp99ssa6) 51

[T73-63 - Using data mining on student behavior and cognitive style data for improving e-learning systems: A case study](#_bqrr5ylvbem9) 52

[T74-64 Title : Using learning analytics to identify successful learners in a blended learning course](#_sga52cd0brse) 54

[T75-65 Title : xxxx](#_jyx3aevyn5oj) 55

[T76-66 Title : Data Mining and Gamification Techniques in Adaptive E-Learning : Promises and Challenges](#_fy1dcchyelxc) 55

[T78-68 Title : xxxx](#_ucjai0b5ptyy) 56

[T79-69 Title : xxxx](#_ezq6tbmqf6hw) 57

[T80-70 Title : xxxx](#_jb3knxxwmwbw) 57

[T81-71 Title : xxxx](#_g4baxet2jzls) 57

[T82-72 Title : xxxx](#_gbp1vtcx3prw) 57

[T83-73 Title : xxxx](#_xxlvb96wudwa) 57

[T84-74 Title : xxxx](#_6sk99okes30q) 58

[T85-75 Title : xxxx](#_2qrag9qcze5x) 58

[T86-76 Title : xxxx](#_yvsh8vgibcio) 58

[T87-77 Title : xxxx](#_jj9ok36lxesg) 58

[T88-78 Title : xxxx](#_u2t6qqm6qhu0) 58

[T89-79 Title : xxxx](#_yytnz6umvjy7) 59

[T90-80 Title : xxxx](#_asou9rkkzg2c) 59

[**Gamification (Game) / Game Based Learning (GBL)**](#_lyi95p4n2fms) **59**

[T101-91 Title : Improving Student Performance through Gamification - A user study](#_36gp22l2lmrp) 59

[T102-92 Title : The effects of gamification elements in e-learning platforms](#_lkoyxw6xdrpa) 59

[T103-93 Title : Gamification in e-learning : A Moodle implementation & its effect on student engagement & performance](#_lkvx5i39pf23) 60

[**Process Mining(PM)**](#_p1e20ari7jch) **60**

[T151-141 Title : Prediction of Student Success Through Analysis of Moodle Logs : Case Study](#_s6mzjs93qfxm) 60

[T152-142 Title : Web usage Mining for Predicting Final Marks of Students that use Moodle Courses](#_3z7exem183p9) 60

[T153-143 Title : Performance Analysis and Prediction in Educational Data Mining: A Research Travelogue](#_dc2csg6ermao) 61

[T154-144 Title : Indicators of Good Student Performance in Moodle Activity Data](#_dkm0d098do9n) 61

[T155-145 Title : Analysis of Student Behavior and Success Based on Logs in Moodle](#_r2xc8yf02sw) 62

[T156-146 Title : Using process mining to analyze students' quiz-taking behavior patterns in a learning management system](#_h9g2cex7nm2) 64

[T157-147 Title : Mining Activity Log Data to Predict Student's Outcome in a Course](#_mm4bbbkxndc6) 64

[**Articles/Thesis**](#_gfbyjpr1wv8e) **66**

[Txx-xx-1 Title : Learning Analytics – Predicting Academic Performance](#_tv3pr1on5dc7) 66

[Txx-xx-1 Title : Prediction of student performance using data mining techniques in higher education domain](#_t3fdbui2nh14) 67

[Txx-xx-1 Title : Possibilities for Improving Student Success Using Predictive Analytics](#_oe9kenzhho7s) 67

[Txx-xx-1 Title : Prediction of Student Performance using Data Mining Techniques in Higher Education Domain](#_m7rswdo68eus) 67

[Txx-xx-1 Title : Predictive Analytics For Student Success : Developing Data-Driven Predictive Models of Student Success : Final Report](#_cfkryw5mvdft) 68

[Txx-xx-1 Title : Developing Data-Driven Predictive Models of Student Success](#_r9l4qvsap7jm) 68

[Txx-xx-1 Title : Data Mining Application for Educational System](#_cmhbi689qskb) 68

[Txx-xx-1 Title : Helping further and higher education organisations to analyse and understand their data](#_1cjdn6et5yu3) 69

[Txx-xx-1 Title : Educational Data Mining/Learning Analytics issue brief overview](#_un6avsw86q5k) 69

[**Heading 1**](#_fgmbij4s0b47) **69**

[Heading 2](#_dknpq1wplc6f) 69

[Heading 3](#_tgfky94t18vx) 69

[Heading 4](#_zaclq3u94ojd) 70

[**T07 LA : Definitions**](#_xyjx1a3rf8xh) **73**

[T12 LA : Applications/ Benefits](#_jl1flnnsjkxi) 81

# 

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# What is learning analytics?

*The term analytics means “the* ***science of logical analysis****” . In practice, analytics encompasses the processes, techniques, and tools used to produce and communicate ‘actionable intelligence’ from large data sets (Campbell, DeBlois & Oblinger, 2007).*

*It is an overarching concept that van Barneveld, Arnold, and Campbell (2012) have defined simply as “data-driven decision making” (p. 8) but which may be more appropriately described as data-informed decision-making given the fundamental role human judgment plays in analytics (Cooper, 2012). (In fact, the* ***emphasis on human interpretation over automation is one of the primary distinctions between learning analytics and educational data mining*** *[Siemens & Baker, 2012; US Department of Education, DOE, 2012]). Cooper (2012) insists that* ***analytics is not just about making decisions, however; it is inclusive of exploration and problem identification.***

[*EDUCAUSE’s*](https://er.educause.edu/blogs/2016/11/the-state-of-learning-analytics) *working definition, is seems to more complete: “****Analytics is the use of data, statistical analysis, and explanatory and predictive models to gain insights and act on complex issues****” (Bichsel, 2012, p. 6).*

*When applied to the education sector,* ***analytics is frequently divided into two distinct but related categories: learning analytics (LA) and academic analytics (AA)****. The term academic analytics was first described by Goldstein and Katz (2005). Learning analytics, according to the US Department of Education (2012) came into use slightly later, in 2009.*

*The Society for Learning Analytics Research (SoLAR, 2011) defines* ***LA as “the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs”*** *(p. 4).*

*LA is more specific than AA,* ***focusing only on the learning process*** *(Long & Siemens, 2011). At academic institutions,* ***LA concentrates on data relevant to students and instructors*** *at the level of the individual learner or course and on* ***using analytic techniques to improve student learning outcomes by better targeting instructional, curricular and support resources and interventions*** *(Elias, 2011; van Barneveld, et al., 2012).*

*Whereas LA is* ***primarily concerned with increasing learner success and the achievement of specific learning goals*** *(van Barneveld, et al., 2012), AA’s aim is analogous to that of business analytics in the corporate sector:* ***increasing organizational effectiveness*** *(Long & Siemens, 2011).*

*SoLAR (2011) defines AA as “the* ***improvement of organizational processes, workflows, resource allocation, and institutional measurement through the use of learner, academic, and institutional***

***data”*** *(p. 4). The* ***focus is not on individual learners or courses****; rather AA is* ***employed at the level of the institution, region or nation****. (SoLAR, 2011, Table 1).*

*In the* ***context of professional training and development,*** *however, the* ***differences between LA and AA are somewhat less pronounced.*** *“From a training industry perspective,” van Barneveld, et al. (2012) explain,* ***LA “focuses on two areas—learning effectiveness and operational excellence*** *—with the latter referring to the metrics that provide evidence of how the training/ learning organization is aligning with and meeting the goals of the broader organization” (p. 6).*

*This bibliography is being compiled by Dhiraj Upadhyaya for pursuing Phd in Learning Analytics and publishing Papers related to it. It is being made in the form of HTML Bookmarks.*

*Currently working on publishing a paper for which I am compiling Annotated Bibliography.*

**PHD - LEARNING ANALYTICS**

# T1 Phd Details

|  |  |
| --- | --- |
| **topic** | **description** |
| **Title** | **Learning Analytics to Predict Performance of Learners in Learning Management System (LMS)** |
| **Problem Statement** | E-Learning is a rapidly evolving field which is capturing more and more data about learners. The study conducted on the latest LMS will provide greater knowledge in predicting Performance among Learners than earlier research. There has to be constant research on this like improving any Business process. A new approach of prediction based on Gamification is being researched. Data Mining methods will be used to explore data |

# T2 Research Objectives

|  |  |
| --- | --- |
| **RO** | **objectives** |
| **RO1** | Investigate the activities which are used often during the learning in LMS courses |
| **RO2** | Compare methods of Learning Analytics in predicting performance of learners in LMS |
| **RO3** | Enhance the LMS framework with Gamification to improve engagement and then predict and assess Performance |
| **RO4** | Use Process Mining to find patterns of Learning to find the best learning traces |

# T3 Research Questions

|  |  |  |
| --- | --- | --- |
| **RQ** | **question** | **RO** |
| **RQ1a** | Which activities does a learner find useful in LMS ? Which are the most used activities ? | RO1 |
| **RQ1b** | What are the learning styles of learners taking a course in LMS ? | RO4 |
| **RQ1c** | How is performance defined in LMS ? What types of metrics and methods are used for describing student performance? | RO2 |
| **RQ2a** | What are the paths taken by learners enrolled in LMS Course ? | RO4 |
| **RQ2b** | What are the Process Mining techniques to analyse LMS Logs for predicting Performance ? | RO4 |
| **RQ3a** | How can dropout rate be predicted from engagement and logs generated in LMS ? | RO2 |
| **RQ4a** | How does Gamification and Game Based Learning increase engagement ? | RO3 |
| **RQ5a** | What is the effect on performance of learners on Courses developed with GBL ? | RO3 |
| **RQ5b** | How much improvement is seen in the dropout rate in such courses ? | RO3 |

# 

# T4 Outcomes of Phd

|  |  |
| --- | --- |
| **OC** | **outcome** |
| **O1** | Comparison of Various Models / Techniques used for analysing a Learner in Education Environment |
| **O2** | Study the various parameters being assessed in LMS (eg Moodle) |
| **O3** | Investigate various Analysis possible using LMS Data and its usefulness for predicting Student Performance and Retention |
| **O4** | Explore the relationship among various activities of LMS in terms of Performance and submission |
| **O5** | Explore the Data Analytics which is provided by Gamification of activities. Suggest Games which improve the Performance of Students |
| **O6** | Suggest a new model based on research conducted and bring out its key features over the existing one. |

# T5 Paper Plan

|  |  |  |
| --- | --- | --- |
| **paper** | **title** | **due** |
| **P1** | **Learning Analytics for Prediction of Student Performance** |  |
| **P2** | **LMS Activities for Learning Analytics** |  |
| **P3** | **Analytics in Learning** |  |
| **P4** | **Prediction of Learners in LMS** |  |
| **P5** | **Gamification as an Activity to Improve and Predict Learner Performance** |  |

# SUMMARY

## T06 Techniques

|  |  |  |  |
| --- | --- | --- | --- |
| **pID** | **area** | **subject** | **description** |
| 0 | LA | Linear Regression |  |
| 0 | LA | Logistic Regression |  |
| 0 | LA | Decision Tree |  |
| 0 | LA | Clustering |  |
| 0 | LA | Association Rule |  |
| 0 | PM | Process Map |  |
| 0 | PM | Trace Explorer |  |
| 0 | PM | Dotted Chart |  |
| 0 | PM | Animate Process |  |
| 0 | PM | Matrix Plots | Precedence |
| 1047 | LA | Logistic Regression | Predict Student at Risk |
| 147 | LA | Naive Bayes |  |
| 147 | LA | Random Forests |  |
| 147 | LA | Ensemble Method | Using Voting System |
| 147 | LA | Clustering |  |
| 34 | LA |  | Predict |

## T08 System/ Application/ Tools

LMS - Moodle, Blackboard; PM- Disco, Bupar : LA - R, Weka, Tableau

|  |  |  |  |
| --- | --- | --- | --- |
| **pID** | **area** | **subject** | **description** |
| 147 | LMS | Moodle |  |
| 27 | LMS | Moodle | almost 80% of institutions had installed LMS with Modular Object-Oriented Dynamic Learning Environment (Moodle) being the most popular (Munguatosha et al., 2011). 47 Moodle sites were institutions from Tanzania (Moodle LMS sites, 2015). |
| 34 | LMS |  |  |
| 35 | LMS | Moodle |  |
| 0 | LMS | Sailka |  |
|  | LMS | Moodle |  |
| 0 | PM | Bupar |  |
| 0 | PM | Disco |  |
| 0 | LA | R |  |
| 0 | LA | Weka |  |
| 0 | LA | Python |  |
|  |  |  |  |

## 

## T09 Area : Activities / Methods Used

LA - Activities; Gamification - Gamification Elements

|  |  |  |  |
| --- | --- | --- | --- |
| **pID** | **area** | **activity** | **descrition** |
| 147 | LA | Assignments |  |
| 147 | LA | Resources |  |
| 147 | LA | Forum |  |
| 147 | LA | Book |  |
| 147 | LA | Quiz |  |
| 147 | LA | Chat |  |
| 147 | LA | Course |  |
| 35 | LA | Resource |  |
| 35 | LA | URL |  |
| 35 | LA | Forum |  |
| 35 | LA | Quiz |  |
| 35 | LA | Sorm |  |
| 35 | LA | Assignment |  |
| 35 | LA | Workshop |  |
| 35 | LA | Wiki |  |
| 0 | GBL | Badges |  |
| 0 | GBL | Levels |  |
| 0 | GBL | Leaderboard |  |
| 0 | GBL | Progress Bar |  |
| 0 | GBL | Virtual Current |  |
| 0 | GBL | Fights |  |
| 0 | GBL | Quiz Venture |  |
| 0 | GBL | Crossword |  |
| 0 | GBL | Flash Card |  |
| 0 | GBL | Student QUiz |  |
| 0 | GBL | MIllionaire |  |
| 0 | GBL | Check LIst |  |
| 0 | GBL | Feedback |  |
|  |  |  |  |

## 

## T10 Factors/ Data for Prediction

|  |  |  |  |
| --- | --- | --- | --- |
| **pID** | **factor** | **effect** | **description** |
| 27 | Peer Interaction | Significant | No of student postings responding to peers |
| 27 | Forum Posts | Significant | Counting a number of posts a students has contributed in the discussion forums |
| 27 | Exercise | Significant | Counting no of exercised a student has done; ( Quiz/ Assignment) |
| 27 | Downloads | Not Significant | No of course materials downloaded |
| 27 | Login Frequency | Not Significant | No of individual student login time in LMS |
| 27 | Time Spent | Not Significant | Total time between login and logout |
| 45 | Clicks |  | Total Number of Clicks (reference) |
| 45 | Online Sessions |  | Number of Online Sessions |
| 45 | Online Time |  | Total Onlne Time (Login / Log Out) |
| 45 | Page View |  | No of course page views |
| 45 | Regularity |  | Regularity of Study Time and Study Interval |
| 45 | Inactivity |  | Largest period of inactivity (minutes) |
| 45 | First activity |  | Time until first activity (minutes) |
| 45 | Avg session Time |  | Average Session Time : total Time/ Total Session |
| 45 | Resources |  | No of Resources Viewed |
| 45 | Links Viewed |  | No of Links Viewed |
| 45 | Discussion |  | Posts/ Read |
| 45 | Quiz |  | Started/ Passed/ Views |
| 45 | Assignment |  | Views / Submitted |
| 45 | Assessment Grade |  |  |
| 45 | Wiki |  | Views/ Posts |
| 34 | Date/ Time of Access | Not Significant |  |
| 34 | Discussion | Significant | Generated / Read / Grade/ No & Type of Ques |
| 34 | Assignment | Not Significant | Grade |
| 34 | Tests | Not Significant | Grade |
| 34 | Email | Not Significant | Email Count to Instructor |
| 147 | Trace Data |  | No of times components was accessed |
| 147 | Assessment Score |  |  |
| 147 | Activities |  |  |
|  |  |  |  |

## 

## 

## T11 xxxxxx

## T13 Gaps/ Future Work/ Suggestions

|  |  |  |
| --- | --- | --- |
| pID | area | futurework |
| 16 | LA | harness data and use it to inform what we do in the classroom, whether face-to-face or online, is at the heart of learning analytics. |
| 34 | LA | Examine Performance and Behaviour indicators at various points in the course instead of doing it in the end |
| 0 | GBL |  |
| 0 | PM |  |
|  |  |  |
|  |  |  |
|  |  |  |
|  |  |  |

## T14 LA : xxxxxxxx

|  |  |
| --- | --- |
| pID | description |
|  |  |

## T15 LA : xxxxxxxx

|  |  |
| --- | --- |
| pID | description |
| 147 |  |

---------------------------------------------------------------------------------------------------------------------

# 

# Templates

## T16 - Template with Sample Data

|  |  |  |
| --- | --- | --- |
| ser | **subject** | description |
| 1.1 | **serial** | 0 |
| 1.2 | **ISSN** | ISSN: International Standard Serial Number (ISSN) is a unique number used to much like ISBN for books. ISSN is used for periodicals, |
| 1.3 | **DOI** | DOI is used for digital objects in general ("digital object identifier") and often for journal articles. |
| 1.4 | **dateA** | Date Added into this Biblio : 01-Jan-20 |
| 1.5 | **dateR** | Date Read : 01-Jan-20 |
| 1.6 | **rating** | Rate the paper Quality 0 - 10 |
| 2.2 | **title** | Title of the paper |
| 2.3 | **area** | PM / LA/ EDM/ LMS/ LS |
| 2.4 | **authors** | Authors in the paper |
| 2.4 | **year** | 2013 |
| 2.5 | **publication** | Computers & Education, 62, 130-148. doi:10.1016/j.compedu.2012.10.023 |
| 2.6 | **type** | Literature Review/ Experimental / |
| 3.1 | **link1** | Publication link (IEEE, Research Gate) |
| 3.2 | **link2** | My Google Docs/ Mendeley |
| 3.3 | **citEEE** | Citation IEEE style  [1] J. Hamari and J. Koivisto, “Social Motivations To Use Gamification: An Empirical Study Of Gamifying Exercise SOCIAL MOTIVATIONS TO USE GAMIFICATION: AN EMPIRICAL STUDY OF GAMIFYING EXERCISE,” ECIS 2013 Complet. Res. 105. , vol. 105, 2013. |
| 3.4 | **citAPA** | Citation APA style  Hamari, J., & Koivisto, J. (2013). Social Motivations To Use Gamification: An Empirical Study Of Gamifying Exercise SOCIAL MOTIVATIONS TO USE GAMIFICATION: AN EMPIRICAL STUDY OF GAMIFYING EXERCISE. ECIS 2013 Completed Research. 105. , 105. Retrieved from http://aisel.aisnet.org/ecis2013\_cr%5Cnhttp://aisel.aisnet.org/ecis2013\_cr |
| 3.5 | **citOthers** | Other methods of citation |
| 3.6 | **paperAvl** | Y (Yes) in pdf, doc form |
| 4.1 | **keywords** | Keywords |
| 4.2 | **abstract** | Abstract |
| 4.3 | **chapters** | Paper Chapters |
| 4.3 | **tags** | tags |
| 5.1 | **RQ** | Research Questions |
| 5.2 | **RO** | Research Objectives |
| 5.3 | **points** | Points from Pape |
| 5.4 | **data** | Types of data |
| 5.5 | **factors** | Factors used for Analysis |
| 5.6 | **methods** | methods/ methodology - |
| 5.7 | **results** | Results from the stuy |
| 5.8 | **conclusion** | conclusion |
| 5.9 | **limitations** | Limitations of the work |
| 6.1 | **futurework** | Authors recommendation for future work |
| 6.2 | **gaps** | Gaps in research, in paper or comments by others |
| 6.3 | **comments** | Any good points |
| 6.4 | **myres** | What I will use in my research |
| 6.5 | **guide** | Comments by guides |
| 6.6 | **highlights** | Highlights in the paper (similar or comments, Publisher points) |
| 6.8 | **refPID** | Referred Paper ID in this document |

## T17 - Blank Table

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| --- | --- |
| **subject** | description |
| **serial** |  |
| **title** |  |

## T18 - Blank Table

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| **subject** | description |
| **serial** |  |
| **title** |  |

## T19 - Blank Table

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| **subject** | description |
| **serial** |  |
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## T20 - Blank Table

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| **subject** | description |
| **serial** |  |
| **title** |  |

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# Papers

## Tables : Start from 21

## Learning Analytics (LA)/ Education Data Mining (EDM) / Learning Management System (LMS)

### TP-1 Title : Factors influencing beliefs for adoption of a learning analytics tool: An empirical study.

|  |  |
| --- | --- |
| **subject** | description |
| **serial** | 1 |
| **dateA** | 01-Jan-2019 |
| **dateR** | 01-Apr-2019 |
| **rating** | 5 |
| **ISSN** | 0360-1315 |
| **title** | Factors influencing beliefs for adoption of a learning analytics tool: An empirical study. |
| **area** | LA |
| **authors** | **Ali, L., Asadi, M., Gaševic, D., Jovanovic, J., & Hatala, M.** |
| **year** | 2013 |
| **publication** | Computers & Education, 62, 130-148. doi:10.1016/j.compedu.2012.10.023 |
| **type** | Conference Paper |
| **link1** | <https://www.sciencedirect.com/science/article/abs/pii/S0360131512002515> |
| **paperAvl** | N |
| **keywords** | quantitative evaluation; E-learning; Feedback; Learning analytics; LAAM Ontologies; |
| **abstract** | Recognizing a lack of empirical research into the factors that influence the adoption of learning analytics tools, Ali, Asadi, Gaševic, Jovanovic, and Hatala present a “first draft” Learning Analytics Acceptance Model (LAAM)—illustrating how educators’ (a) pedagogical knowledge and information design skills, as well as their perceptions of a LA tool’s (b) usefulness and (c) ease-of-use affect their behavioral intention to use the tool in their courses.  In this study, data were collected from a sample of 22 instructors, teaching assistants and researcher /learning analysts from three universities and a private Canada-based company that develops and offers technology and content for professional training. The participants experimented with a Learning Object Context Ontologies (LOCO)-Analyst tool, which provides context-specific analytics on students’ activities and social interactions in the online environment and on the usage and comprehensibility level of learning content. (The article’s appendix contains a useful overview of LOCO-Analyst.) Ali et al. used a questionnaire-based survey instrument to measure the elements  of the LAAM and conducted statistical analyses of the participants’ responses.  The results of their research suggest that what educators value most is straight-forward information about student-student interactions and students’ comprehension of course content. Participant responses indicated that the tool enabled them to gain insight into students’ online interactions but was less useful in terms of identifying how to address suboptimal interactions.  Although the authors had hypothesized that educators’ usage beliefs (i.e., usefulness and ease-  of-use perceptions) about the tool’s learning analytics would positively influence their intention to adopt it in practice, analysis of the data revealed that the usefulness and ease-of-use perceptions were not significant indicators of the intention to use LOCO-Analyst. The one exception was participants’ perception of whether the tool would help them identify what in the learning content needed improvement (r = 0.77, p < .01). While the LAAM model clearly needs refining and the study needs replicating with other populations and analytics tools before drawing any definitive , |
| **comments** | the article was nevertheless published in a leading journal as an early contribution to the research community’s efforts to understand the acceptance and adoption of learning analytics tools—an area in which there is still much work to be done, and which has practical relevance for education practitioners. |
| **highlights** | Gives empirically validated models of the factors influencing tool adoption beliefs. Those engaged in teaching are better placed to internalize perceived tool utilities. Users appreciate tools that provide some hints on how to improve online courses. ►No significant relationship between ease-of-use belief and intention is observed. |

### T12-2 Title : Improving the Student Experience with Learning Analytics in Construction Project Management Courses

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| --- | --- |
| **subject** | description |
| **serial** | 2 |
| **link1** | <https://easychair.org/publications/open/XgvK> |
| **area** | LA |
| **title** | Improving the Student Experience with Learning Analytics in Construction Project Management Courses |
| **year** | 2017 |
| **abstract** | Learning analytics is an emerging field that has been gaining momentum in higher education. Learning analytics is the analysis and reporting of learner related data. Research has examined the benefits of learning analytics in higher education but there **has been limited research conducte**d about the impact of showing students their own learning data. The aim of this study was to provide students with their own learner data, obtain feedback about the usefulness of this information and investigate if providing learning data leads to an increase in self-efficacy and self-reflection. The  sample consisted of 78 students studying construction management, project management, and property and valuation. Students were provided with weekly learner reports that included data about their behaviour in a learning management system, their level of interaction in lectures, and their performance on assessments. A suggested target was provided toward an individualised behaviour goal, as well as comparison with both the contemporary class average and previous class averages.  Students completed measures of self-efficacy and self-reflection pre and post intervention and feedback about the reports was obtained through surveys and a focus group. Results showed no significant change in self-efficacy and self-reflection, however, student**s reported finding the learning analytics reports helpful**, believed it helped them reflect on their own learning and wanted to see more analytics in other subjects. Results support the use of learning analytics in the classroom and suggest that they may enhance the student experience |
| **keywords** | Learning Analytics, Higher Education, Construction Project Management |
| **data** | Information about student performance or learning behaviour can be collected from a range of different sources. Data has traditionally included student enrolment data, academic records, student surveys, and data from online discussion boards. Data about student behaviour can also be obtained from students’ interactions with university learning systems (Aljohani & Davis, 2012).  The LMS was used in this course to provide learning resources, including readings and lecture recordings as well as assessment tasks, rubrics and guides. Students submit their assessment tasks via the LMS. |
| **purpose** | purpose of this study was to provide students with personalised data from a range of  contexts, including behaviour in an LMS, assessment performance, and interaction in lectures. As well as individual data, students were also provided with class comparison data. This project aimed to use these learning analytics to promote learner self-reflection and self-efficacy. In addition the study sought feedback from students on the perceived value of this data. |
| **methods** | Students in a first-year undergraduate construction management course at a large Australian university were invited to participate in the research. Of the 151 students enrolled in the course, 78 students (23 female, 53 male and 2 other) agreed to participate in the study. Participants ranged in age from 18 to 25  Learner data reports were provided by email at the end of each week throughout the 12-week semester. The learner data was collected from three different sources: LMS, lecture participation and weekly assessment performance (described in detail below). Student self-efficacy and self-reflection were measured at the beginning and end of the semester. An action research approach was used (Kemmis & McTaggart, 1988). A cyclical (plan, act, observe, reflect) and participative model was adopted, with students actively engaged to help construct and improve the learner reports throughout the semester  The research team extracted learner data available on the LMS including total number of times students have accessed different areas in the LMS and the breakdown of total hours per week. This data was presented to students visually as individualised data. This information provides data about student behaviour but it does not indicate the level of engagement with the material. The class average was also provided for comparison |
| **results** | Results of the end of semester survey showed that students valued the learner reports and these reports were perceived to have a positive impact on their learning. In total, 78% of students rated the learner data reports as helpful and the same number rated the reports as useful in reflecting on their own learning. The majority of students (80%) reported that they would like to see similar learner data reports in their other classes. One suggestion by the students was that they would like to see a learner report that incorporated data from all of their courses, providing a holistic picture of their academic progress.  Most of the students found the learner reports helpful. 44% of students rated the learner data reports that they received as ‘very helpful, 33% of students rated the data reports as ‘somewhat helpful,’ 11.% of students rated the helpfulness of the reports as ‘neutral’ and 11% of students rated them as ‘somewhat unhelpful.’ These findings suggest that, overall students found the reports helpful.  A small percentage of students (11%) did not find the learner reports helpful. Further interrogation revealed that these students were not progressing well in the course and were either failing or just passing. Follow up conversations with these students indicated that the learner report was not perceived to offer any new information – these students already knew they were not doing well. In the focus group students suggested that they would have liked suggestions for how to improve and links to resources and support. They also recommended that the reports form the basis for a follow up conversation with teaching staff focused on suggestions for improvements in their studies. The majority of students (78%) opened their emails about learner data and most of the students (65%) reported that they were opening their reports on a weekly basis. This suggests there was a considerable interest in students seeing their learner’s data. The anecdotal conversations with the students throughout the research implementation phase also confirmed this interest. While students appeared to appreciate the learner data and perceived it as useful for their learning, comparison of scores on the Generalised Self Efficacy Scale and Self-Reflection and Insight Scale revealed only small improvements over time. Neither was significant.  **Students reported that they felt that self-reflection would have increased if the reports had been discussed in class.** Students felt that discussion in class would have provided a deeper understanding of the reports and a greater chance to interpret what they meant. **Students reported that they liked being able to see how they compared to other students as it gave a better sense of their performance and they could track when other students found certain assessments difficult.** Particularly, this comparison is helpful for the first year and exchange students who have not yet created their networks. The reports provide them with a benchmark to that they can compare themselves. |
| **conclusion** | **Learning analytics has been viewed as having the potential to change learning and teaching in higher education.** Higher education institutions have used learning analytics primarily to identify and address the challenges the students face. These applications of learning analytics are predominantly developed from an educator’s perspective. However, there are potential benefits to directly sharing analytics with students.  This research **investigated the use of learning analytics to enhance the student experience.** A large cohort of students in a construction project management course were chosen for the study. The learner’s data were analysed and feedback to students. Student feedback was sought throughout the project implementation and at the end of the semester through student surveys. A focus group was held to receive in depth feedback from students.  Overall, the **results indicated that students valued the learner reports they received and felt that it had a positive impact on their learning.** This is an important finding as it demonstrates that students are interested in their own learning behaviour and that learning analytics may be useful for students as well as staff. Based on the current findings learning analytics may improve the student experience  Most students reported that the learner reports helped them reflect on their own learning and the majority students reported that they would like to see similar learner data reports in their other classes. These findings confirm the usefulness of such reports and demonstrate that, when used appropriately, learning analytics has the potential to help students engage in their own learning. |
| **limitations** | The results did not show any significant changes in self-efficacy or self-reflection. The information provided to students did not increase their belief in their ability to achieve. There are a number of potential reasons for this. The information provided to the students did not provide any tips, suggestions or ideas about what to do with the information they received. It may have been beneficial to have given students direction about what to do to help change their behaviour. For example, students with low scores on assessments could have been provided with links to services or tips on how to help improve their learning or scores. It may have also been that students did not process the information in the learner reports. The only data we have available is about how often the emails were accessed. By itself, this information is limited and tells us little about how students engaged with the material. It may have been beneficial to have discussed the learner reports in class to help strengthen student understanding and engagement with the reports |
| **comments** | The research has demonstrated that learning analytics can enhance the learning experience. Students suggested a better analytics report in which a single report integrates all their analytics from all courses. |
| **futurework** | To our knowledge, this is the first study that has actively shown students their own learner data. Providing learner’s data to the learner is a new area that creates new dynamics in classrooms. Participants of this study suggested follow up conversations with the instructor after they received their reports. This opens **new areas of work for student experience enhancement and introduces new dynamics to the classrooms that require further investigation.** |
| **publication** | EPiC Series in Education Science |
| **ISSN** |  |
| **rating** | 8 |
| **myres** | Good conclusion, can be used; |
| **RQ** | Can LA enhance the learning experience ? |
| **RO** | Study the effect of sharing learner data with students |
| **tags** | LA, LMS, Moodle |
| **dataR** | 08-May-20 |

### T13-3 Title : Course Signals at Purdue: Using learning analytics to increase student success

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| **subject** | description |
| **serial** | 3 |
| **title** | Course Signals at Purdue: Using learning analytics to increase  student success |
| **area** | LA |
| **authors** | **Arnold, K. E. & Pistilli, M. D. (2012).** |
| **year** |  |
| **publication** | In S. Buckingham Shum. D. Gašević, & R. Ferguson (Eds.), LAK '12  Proceedings of the 2nd International Conference on Learning Analytics and Knowledge  (pp. 267-270). New York, NY: ACM. doi: 10.1145/2330601.2330666 |
| **abstract** | In this conference proceedings paper, Arnold and Pistilli discuss the early warning student intervention system, Course Signals (CS). Signals uses a predictive student success algorithm (SSA) to calculate students’ risk level in a class based on SIS and LMS data on their current course performance, effort compared to peers, academic history, and demographic characteristics. When the instructor runs the SSA, each student in the class is assigned a visual risk indicator (a red, yellow, or green traffic signal icon) corresponding to his or her likelihood of success.  Instructors can send accompanying written messages with student-specific feedback, information, and resources for improving performance. When Arnold and Pistilli combined the final grade distributions of all courses using Signals in a given semester, they found a 10.37% increase in A’s and B’s compared to the same courses before Signals was implemented. They also found a 6.41% decrease in D’s, F’s and withdrawals compared to pre-Signals semesters of those same courses. Additionally, first-time, full-time students who matriculated at Purdue in 2007, 2008 or 2009 and  took at least one course in which Signals was used persisted in their studies at significantly higher rates than cohort peers who did not participate in a Signals-enabled course; students who took two or more Signals courses consistently persisted at higher rates than peers who took one or none. Additional analyses revealed that the earlier a student took a Signals course in their academic career, the greater the likelihood they were retained into the next semester. Perhaps most compelling are early indications that lesser-prepared students in a Signals-enabled section of a difficult course are more successful than better-prepared students in a class without Signals.  Across five semesters, Purdue has received anonymous survey feedback from 1,500 students on their experience of Signals. 89% of student respondents report that Signals provided a positive experience and 58% said they would like to have it in every course they take. Negative feedback pertained to the way faculty had used it (e.g., redundant e-mail, text, and LMS messages; not updating traffic signals after running the SSA; lack of specificity in the messages). Course instructors are also mostly positive about Course Signals but some have expressed concerns about receiving “an excess of e-mails from concerned students”, “creating a dependency in newly arrived students” and “a lack of best practices for using CS” (p. 4). Purdue has assembled a list of best practice tips to address this last issue.  While not without shortcomings, Purdue Course Signals is a laudable example of how analytics can have a practical and measurable impact on student success. |

### T14-4 Title : Educational Data Mining & Students’ Performance Prediction

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| **subject** | description |
| **serial** | 4 |
| **title** | Educational Data Mining & Students’ Performance Prediction |
| **area** | EDM |
| **link2** | <https://thesai.org/Downloads/Volume7No5/Paper_31-Educational_Data_Mining_Students_Performance_Prediction.pdf> |
| **comments** | explores multiple factors theoretically assumed to affect students’ performance in higher education, and finds a qualitative model which best classifies and predicts the students’ performance based on related personal and social factors. |

### T15-5 Title: Machine Learning Approaches to Predict Learning Outcomes in Massive Open Learning Courses

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| **subject** | description |
| **serial** | 5 |
| **title** | Machine Learning Approaches to Predict Learning Outcomes in Massive Open Learning Courses |
| **comments** | MOOCs provide alternative learning platform. Learners from across the globe can access same quality of learning through the web.  Large volume of data is collected and capture from MOOCs - viewing content, undertaking quiz’s, discussion forums etc  Data from MOOCs can provide valuable info educators by analysing patterns present in the behaviour of learners  Various methods utilised by researchers - AI, Web analytics, Social Network Analysis  Can draw inferences about student performance with deeper insight  Still challenging to build predictive models in MOOCs. |

### T16-6 Title: Learning Analytics in a Smart Classroom to Improve eEducation

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| **subject** | description |
| **serial** | 6 |
| **area** | LA |
| **dateR** |  |
| **rating** |  |
| **title** | Learning Analytic in a Smart Classroom to Improve eEducation |
| **link1** | http://ieeexplore.ieee.org/document/7962510/ |
| **comments** | Teaching and Learning in a course can produce a lot of information about the learning process and the main question is how to explore it.  LA provides answers to Qs like  How does the information collected during a learning process can enrich students learning experiences  How can an Educational Institution effectively exploit the data collected in a course in order to positively impact the teachers pedagogical practices  LA uses statistical techniques, machine learning approaches, data visualisation techniques, among others to provide knowledge which will help to optimize student performance to highlight  students problems,  Improve pedagogical strategies  Tune up educational platforms  LA can improve the teaching and learning process using educational data, because it provides a window of knowledge about what takes place over the trajectory of student learning  Smart Classroom have different components (which adapts & integrates to the course according to the necessities of the students)  Hardware (smart boards, cameras)  Software (Intelligent Tutoring Systems)  Virtual Learning Environment (VLE)  Repositories of Learning Objects  Recommender Systems of Edn resources  It is possible to apply LA tasks to define the teaching principles or teaching methodologies of students in a smart classroom  What data does a Smart Classroom generate ?  How do we apply LA into it to study Student Behaviour |

### T17-7 Title: Big Data and analytics in higher education: Opportunities and challenges

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| **subject** | description |
| **serial** | 7 |
| **title** | Big Data and analytics in higher education: Opportunities and challenges |
| **area** | EDM |
| **authors** | Ben Daniel |
| **year** | 2014 |
| **publication** | British Journal of Edn Technology |
| **abstract** | Institutions of higher education are operating in an increasingly complex and competitive environment. This paper identifies contemporary challenges facing institutions of higher education worldwide and explores the potential of Big Data in addressing these challenges. The paper then outlines a number of opportunities and challenges associated with the implementation of Big Data in the context of higher education. The paper concludes by outlining future directions relating to the development and implementation of an institutional project on Big Data. |

### T18-8 - Title:Comparative Analysis of the Effect of Attendance on Academic Performance of Management and Finance Course Students

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| **subject** | description |
| **serial** | 8 |
| **title** | Comparative Analysis of the Effect of Attendance on Academic Performance of Management and Finance Course Students |
| **area** | EDM |
| **keywords** | Academic Performance Attendance Teacher-Student Interaction Personality |
| **abstract** | The fact that attendance has a positive effect on the performance of students has been studied by many researchers. This paper provides some evidence on the assumption that the subject of finance requires more teacher-student interaction than the subject of management. Thus attendance and academic performance has more strong relationship for finance than for management subjects. The 170 responses collected from students were analyzed through OLS technique. A stronger positive relationship of attendance and performance was found for Finance as compared to Management. The findings can be applied for other subjects, keeping in view the technicality and non-technicality of the subjects. The limitation in the research has been the variability in the personality of teachers and also the students, which can be very difficult to measure correctly and thus the finding can be different in different scenarios. |
| **results** | The data was tested for t-test, probability, F-statistics, Durbin-Watson and significance factor through applying Ordinary Least Square (OLS) technique. The technique was used for each course separately, for the combined data of both the subjects and for the relationship of age with each subject separately. In all cases, the findings (attendance and marks) were positively related; it was significant with all the other tests. The OLS method has been used by other researchers with slightly more or less variables. And most of the time the research has been carried out for the subjects of Economics.  The econometric technique used in this research was focused on finding the comparative analysis of two subjects, i.e. management and finance for their relationship with students’ attendance and performance (marks). The hypothesis was that the subject of finance has a stronger positive relationship with the attendance of the students than the subject of management.  The reason behind this is the point of view that finance is more technical and requires more teacher-student relation as compared to the subject of management. It might not be the case with students in their last semesters with finance as a core subjects, but still it might be. This is the point yet to be tested.  The values of F-stat which are 13.43 for Management and 19.08 for the subject of Finance show a significant effect on academic performance due to attendance. And in this case the subject of Finance has a stronger relation than Management. The Durbin-Watson tests for both Management and Finance are close to 2.0, showing low correlation. And in comparison the subject of Finance has been closer to the value of 2.0 than Management.  Table 2 shows the results of the tests that were carried out to find the significance and appropriateness of the model used. The three variables that were used have been tested for their contribution in creating the impact on the performance along with the attendance.  The results of the research shows that with one unit increase in the attendance, there is.705 unit increases in the marks of students in the subject of finance and for the same one unit increase the marks of the students showed an increase of.665 units for the subject of management. Thus the current study proved that the subject of finance requires more student-teacher interaction for better academic performance than the subject of management. Or we can say that attendance is strongly related to the marks in case of finance than the subject of management.  Implication: In this study, Ordinary Least Square (OLS) technique was used to find the relation separately for each subject and then an overall impact was also found. The results show that students of finance scored high with high attendance and the relation was strong while it was not the case with the management. The relation was there, but not that strong as it was in the subject of finance. It has been clearly derived from the analysis that the Another factor is the difference of the attitude subject of finance has a stronger relationship with the attendance of students than the subject of Management based on the understanding that Finance is more technical than Management. With this feeling about the subject, students have a psychological fear for less learning in case of missing the lectures. This was the concept behind this research which got proved by studying the data. This study was carried out where an enforced policy of attendance was prevailing. This fact is already proven that in an enforced policy the attendance and performance scores increases while it drops in a non enforced attendance policy. But this does not affect their relationship.  The study shows the relationship of two subjects in comparison, which can be extended to more than two subjects. Also different kinds of subjects can be compared for further analysis. And the findings can be used for policy making regarding compulsory attendance of one or more subjects.  The other implication from this study is that credit hours of different subjects can be adjusted according to the difficulty level. And thus those subjects can be identified which require more student- teacher interaction and vice versa. Thus the education system can be made more efficient and effective. This was the core idea behind this effort which needs to be verified again and again for the practical implications of the findings.  Limitations: The first limitation of this study is the number of variables, which are very few. The number and kind of variables can be increased and thus the results might be different. Secondly, the selection and number of subjects is also conveniently selected with minimum randomness. More than two different subjects can be used for future study. Sample size is also too small. In future, sample size can be increased for more reliable results.  Though in most of such studies the OLS technique has been used with different data sets, it could be the third limitations if another better statistical model can be developed.  Another factor is the difference of the attitude towards learning of the students in different parts of the world. Thus this factor can also make the finding different in different parts of the globe. |

### T19-9 Title : An analysis of some factors affecting student academic performance in an introductory biochemistry course at the University of the West Indies

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| --- | --- |
| **subject** | description |
| **serial** | 9 |
| **title** | An analysis of some factors affecting student academic performance in an introductory biochemistry course at the University of the West Indies |
| **area** | EDM |
| **keywords** | high failure rates, introductory biochemistry, learning preferences, mature students, gender, entry qualifications. |
| **conclusion** | None of the selected factors investigated in this study had a significant effect on the academic performance of students in the introductory biochemistry course. The list of factors investigated was not exhaustive, for there are several other factors that can influence academic performance. Further analysis of these other factors that are known to influence academic performance (such as student motivation, socioeconomic status, and attendance) is required. The to be drawn from this study are that gender, age, learning preferences, and entry qualifications did not cause any significant variation in the academic performance of students.  Although their academic performance was not significantly different from the rest of the students, holders of the diploma in agriculture seem to consistently lag behind the rest of the students. A closer analysis of the challenges faced by these students may be worthwhile. If required, a remedial course can be offered to these students as a corrective measure to ensure that they are equally well-equipped to handle the demands of AGRI 1013. |
| **comments** | High failure rates at tertiary institutions result in unacceptable levels of attrition, reduced graduate throughput and increased cost of training a nation’s labour force. It is imperative that diagnostic studies are carried out to identify the major factors that are associated with suboptimal academic performance with a view of instituting corrective measures. This study was, therefore, designed to identify and analyse some determinants of academic performance (as measured by coursework exam grades) in an introductory biochemistry (AGRI 1013) course plagued by chronic high failure rates. The course is offered to first year undergraduate students in the Faculty of Science and Agriculture at the University of the West Indies, St. Augustine campus. A survey instrument was administered to a random sample of 66 registered students of AGRI 1013 (representing a 40% sampling fraction) to generate data on demographics (gender and age), learning preference, and entry qualifications. The effect of learning preference, age, gender, and entry qualifications on academic performance (measured as the final coursework mark obtained) was determined. Relationships/associations between gender and learning styles, gender and entry qualifications, age and learning preferences, and age and entry qualifications were analyzed using Pearson’s chi-square test. There were significant (P < 0.05) associations between entry qualifications and both gender and age. However, since entry qualifications did not significantly (P > 0.05) affect academic performance, this association should be of limited concern.  None of the investigated factors significantly affected academic performance. This observation could be a consequence of an impressive performance in the coursework exams by a large proportion of students resulting in less variation in the recorded grades. Learning preferences were found to be independent of both the age and gender of students. It was concluded that more determinants of academic performance need to be investigated and that students who are admitted based on a diploma in agriculture may need a remedial course given that their coursework grades, though statistically insignificant were consistently lower than that of the other students |

### T20-10 Title : An analysis of some factors affecting student academic performance in an introductory biochemistry course at the University of the West Indies

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| --- | --- |
| subject | description |
| serial | 10 |
| rating |  |
| title | An analysis of some factors affecting student academic performance in an introductory biochemistry course at the University of the West Indies |
| abstract | An increase in hybrid course offerings at WCTC was part of the 2010 WCTC Budget document. The purpose of tills study was to analyze the effectiveness of student performance in hybrid(Blended) and traditional classroom accounting courses at WCTC.  Research questions attempted to determine whether or not there was a difference in performance between the on campus and hybrid student population. The first research question compared student performance based on a hybrid or traditional course delivery. The average grade earned by students from the hybrid course was a half grade higher when compared to the students in the traditional course. The second research question examined the impact of gender on student success. The females earned a higher average grade compared to their male counterparts in both the traditional and hybrid course. The third research question compared the impact of age. Older students earned higher grades then the younger students. The fourth research question examined the impact of grade point average. Grade point average was a good indication to determine the success of the students. It is recommended to conduct additional research to determine the generalizability of students in hybrid courses earning higher grades then the students in the traditional courses. |
| results | The purpose of the study was to measure the effectiveness of the Accounting IV Intermediate course delivered in a hybrid format compared to an Accounting IV Intermediate course delivered in traditional classroom format at Waukesha County Technical College. Hybrid course development was a current initiative at WCTC. |
| comments | Summary and  The participants in this study consisted of 17 students who enrolled in the Accounting IV Intermediate course in the fall of 2009. There were 12 females and 5 males participating in the study. The age of the students ranged from 19 to 46 years old. Twelve students were enrolled in the traditional classroom course and six students were enrolled in the hybrid course.  The four research questions are addressed below.  Research Question 1. How do WCTC students perform in a hybrid course compared to  traditional course in the delivery of the Accounting IV course? The average grade earned by  students from the hybrid course was a half grade higher when compared to the students in the traditional course. The sample size was small due to the limited number of hybrid course  offerings.  Research Question 2. Does gender have an impact on student success with hybrid and  traditional courses? Both females and males scored higher in the hybrid course versus the  traditional course. The females earned a higher average grade compared to their male  counterparts in both the traditional and hybrid course.  Research Question 3. Does age have an impact on student success with hybrid and traditional courses? All three As earned were by students who were 30 or older and enrolled in the hybrid course. Grades of C or lower were earned by students who were 29 or younger. The limited data is this study suggests the older students will earn higher grades then the younger students.  Research Question 4. Does cumulative grade point average have an impact on student  success with hybrid and traditional courses? All three As were earned by students who had a cumulative grade point average of 3.5 or better. The students who had a cumulative grade point average below 2.5 earned a D- and a withdraw grade.  Recommendations  The findings of this study demonstrate the hybrid courses are an effective if not more effective method than traditional courses. As a result, the hybrid courses should continue to be offered. As matter of fact, more hybrid courses should be developed to meet the needs of the students. This study was very limited in the number of students enrolled in the traditional and hybrid course due to the limited offerings of the hybrid courses. Waukesha County Technical College should continue to increase the number of hybrid courses and continue to study student achievements in each.  The traditional classroom assessments and hybrid assessments do have some differences.  The instructors need to be aware how to effectively complete student assessments in a hybrid format. Additional training or workshops should be completed by instructor prior to teaching a hybrid course.  Further studies should be performed to ensure these early trends in student success with hybrid courses continue. The increase of hybrid course offerings at WCTC will provide more data for another study to compare the effectiveness of traditional and hybrid courses. The next study should include a greater number of participants which should be available with all the new hybrid course offerings coming up at WCTC. |

### T21-11 Title: Personalized Multi-Regression Models for Predicting Students’ Performance in Course Activities

|  |  |
| --- | --- |
| **subject** | **description** |
| serial | 11 |
| area | LA |
| keywords | Regression with multi-regression models, Analyzing student behavior, Predicting student performance |
| title | Personalized Multi-Regression Models for Predicting Students’ Performance in Course Activities |
| abstract | Methods that accurately predict the grade of a student at a given activity and/or course can identify students that are at risk in failing a course and allow their educational institution to take corrective actions. Though a number of approaches have been developed for building such performance prediction models, they either estimate a single model for all students based on their past course performance and interactions with learning management systems (LMS), or estimate student-specific models that do not take into account LMS interactions; thus, failing to exploit fine-grain information related to a student’s engagement and effort in a course. In this work we present a class of linear multi-regression models that are designed to produce models that are personalized to each student and also take into account a large number of features that relate to a student’s past performance, course  characteristics, and student’s engagement and effort. These models estimate a small number of regression models that are shared across the different students along with student-specific linear combination functions to facilitate personalization. Our experimental evaluation on a large set of students, courses, and activities shows that these models are  capable of improving the performance prediction accuracy by over 20%. In addition, we show that by analyzing the estimated models along with the student-specific combina-  tion functions we can gain insights on the effectiveness of the educational material that is made available at the courses of different departments. |
| comments | In this work, we have used a multi-regression model to predict student performance in course activities and analyze the resulting student populations. We have shown that a multi-  regression model performs better than single linear regression as it captures personal student differences through the student-specific membership weights. We have also shown  that the RMSE tends to decrease with increasing the number of linear regression models and thus allowing room for more personalized predictions. We have also shown that  using the Moodle interaction features lead to an improved prediction accuracy.  Analyzing the estimated parameters of the multi-regression model showed that the student bias, course bias and features related to viewing the course material are the factors that mostly contribute to the predicted grades. The analysis also showed that the activity-specific features had different contributions within the different linear models. Moreover, the analysis of the different student populations showed that the features relating to viewing of course material contribute to the predictions of a certain student subpopulation higher than other students. It also appeared that some departments tend to have students whose viewing of course material contribute to their predicted grades less than other students. This might indicate that the material provided in the LMS for these departments may not be addressing  the right student needs and thus are not helping students achieving better grades. |

### T22-12 Title: Applying Web-Mining Methods for Analysis of Student Behaviour in VLE Courses

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| --- | --- |
| subject | description |
| serial | 12 |
| title | Applying Web-Mining Methods for Analysis of Student Behaviour in VLE Courses |
| keywords | virtual learning environment, collaborative learning, constructivist pedagogy, web-mining method |
| abstract | In Hungary, a lot of electronic-based syllabuses have been developed during the last 8-10 years at a most considerable cost. However, not much has been heard of their success or efficiency, as would be supported by scientific testing. First, the present study is to provide a survey of our project, which aimed at creating an integrated electronic learning environment. The processing of an education technology syllabus integrated in the Moodle virtual learning environment system took place in the passing academic year. The analysis of student behaviour in the learning environment is based on log files created on the server during the course of interaction between learners and the electronic syllabus. We analysed the learning activity of the students in the learning environment in exact numeric terms by using methods of web-mining. The second part of the study presents some of our first empirical results in this field. |

### T23-13 Title: An Educational Data Mining Model for Predicting Student Performance in Programming Course

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| --- | --- |
| subject | description |
| serial | 13 |
| title | An Educational Data Mining Model for Predicting Student Performance in Programming Course |
| area | EDM |
| keywords | Data Mining, Student Performance, Programming Course, Rule Extraction. |
| abstract | This paper presents an educational data mining model for predicting student performance in programming courses. Identifying variables that predict student programming performance may help educators. These variables are influenced by various factors. The study engages factors like students' mathematical background, programming aptitude, problem solving skills, gender, prior experience, high school mathematics grade, locality, previous computer programming experience, and e learning usage. The proposed model includes three phases; data preprocessing, attribute selection and rule extraction algorithm. |
| conclusion | The ability to predict an individual’s potential to learn programming concepts is important for many reasons. Identifying variables that predict student programming performance may help educators and employers select potential students and employees. Curriculum committees can use prediction results to guide changes to the curriculum and evaluation of the effects of those changes. Data mining can be used to discover novel relationships that my exist in the data and possibly to improve the generalization of solution. This study investigates the potential of data mining for enhancing the effectiveness of academic planners and level advisers in higher institutions of learning. Students' data in the department of computer science from Mansoura University are collected over three academic years and data mining algorithm is applied to extract rules predicting students' performance in programming course. A set of accurate and comprehensible rules is obtained. The machine learning algorithm extracts only the rules which have the antecedent(s) satisfy 100 % of the conditional probability within certain class. The extracted rules confirm the important of variables such as High School Mathematics Grade and programming aptitude. Educators should tack these variables into account in the qualifying exam to join computer science departments at universities. |

### T24-14 Title: Factorization Models for Forecasting Student Performance

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| --- | --- |
| subject | description |
| serial | 14 |
| area | LA |
| title | Factorization Models for Forecasting Student Performance |
| abstract | Predicting student performance (PSP) is one of the educational data mining task, where we would like to know how much knowledge the students have gained and whether they can perform the tasks (or exercises) correctly. Since the student’s knowledge improves and cumulates over time, the sequential (temporal) effect is an important information for PSP. Previous works have shown that PSP can be casted as rating prediction task in recommender systems, and therefore, factorization techniques can be applied for this task. To take into account the sequential effect, this work proposes a novel approach which  uses tensor factorization for forecasting student performance. With this approach, we can personalize the prediction for each student given the task, thus, it can also be used for recommending the tasks to the students. Experimental results on two large data sets show that incorporating forecasting techniques into the factorization process is a promising approach. |
| comments | Predicting student performance is an important task in educational data mining, where we can give the students some early feedbacks to help them improving their study results. A good and reliable model which accurately predicts the student performance may replace the current standardized tests, thus, reducing the pressure on teaching and learning for examinations as well as saving a lot of time and effort for both teachers and students.  From educational point of view, the learner’s knowledge improves and cumulates over time, thus, sequential effect is an important information for predicting student performance. We have proposed a novel approach - tensor factorization forecasting - which incorporates the forecasting technique into the factorization model to take into account the sequential effect. Indeed, factorization techniques outperform other state-of-the-art collaborative filtering techniques [Koren 2010]. They belong to the family of latent factor models which aim at mapping users (students) and items (tasks) to a common latent space by representing them as vectors in that space. The performance of these techniques are promising even we do not know the background knowledge of the domain (e.g. the student/task attributes). Moreover, we use just two or three features such as student ID, task ID and/or time, thus, the memory consumption and the human effort in pre-processing can be reduced significantly while the prediction quality is reasonable. Experimental results have shown that a combination of factorization and forecasting methods can perform nicely compared to previous works which only use factorization techniques.  Another advantage of this approach is that we can personalize the prediction for each student given the task, and thus, besides predicting student performance, one could use the proposed methods to recommend the tasks (exercises) to students when building a personalized learning system. A simple forecasting technique, which is moving average, was incorporated into the factorization model. However, applying more sophisticated forecasting techniques, e.g. Holt-Winter [Chatfield and Yar 1988; Dunlavy et al. 2011], may produce better results. |

### T25-15 Tile : Mining Educational Data to Predict Students Academic Performance using Ensemble Methods

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| --- | --- |
| **subject** | **description** |
| serial | 15 |
| year | 2005 |
| area | LA |
| title | Mining Educational Data to Predict Students Academic Performance using Ensemble Methods |

### T26-16 Title : Learning Management System With Prediction Model And Course-content Recommendation Module

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| --- | --- |
| **subject** | **description** |
| serial | 16 |
| year | 2017 |
| DOI | https://doi.org/10.28945/3883 |
| link1 | <http://www.jite.org/documents/Vol16/JITEv16ResearchP437-457Evale2945.pdf> |
| area | LA |
| title | LEARNING MANAGEMENT SYSTEM WITH PREDICTION MODEL AND COURSE-CONTENT  RECOMMENDATION MODULE |
| purpose | This study is an attempt to enhance the existing learning management systems today through the integration of techno |
| methods | The author used two models for the system development: these are the Fayyad knowledge discovery in databases (KDD) process model for the data miningphase and the evolutionary prototyping for system development. WEKKA and SPSS were used to find meaningful patterns in the historical data, while Ruby on Rails platform was used to develop the software |
| results | The result shows that J48 was the best data mining algorithm to be implemented  for finding patterns in the data sets used in this study. Attributes such as age, gender, class schedule, and grades in other programming subjects were found relevant in predicting student performance in Java |
| keywords | learning management systems, educational data mining, prediction model, performance prediction, attribute selection, course-content recommendation, index  of learning styles |
| futurework | Study about the impact of implementing this LMS in classroom environment will be conducted on the second phase |
| factors | With these data, the researcher came up with following attributes as significant predictors: age, gender, schedule, grade in Programming 1, grade in Programming 2, and grade in Programming 3. |
| dmmethod | C4.5, which is one of the most widely-used classification algorithms (Smith & Bull, 2003), gave birth to J48 - an improved implementation of a decision tree classifier that can be used for predicting performance. J48 gained popularity because of its high percentage of correct prediction, optimized decision tree diagram, and straightforward rule sets which do not need complicated interpretation (Rajput, Aharwal, Dubey, Saxena, & Raghuvanshi, 2011). The result in Table 6 shows that in predicting the performance of students in Java programming, J48 is the best algorithm to be used since it has the highest percentage of accuracy in making predictions and at the same time has the highest Cohen’s kappa. Kappa value of 0.8464 means that the prediction is strongly reliable with sixty-four to eighty-one percent reliability based on the suggested Cohen’s kappa interpretation of McHugh (2012). |
| limitations | This LMS for Java programming with a prediction model and course-content recommendation module was able to meet the ideal requirements for generating predictions and recommendations. There are some limitations in resources and time constraints. Encountered limitations are as follows: 1. Intrinsic attributes of the learners are not included as factors for predicting their performance. 2. Recommendations is limited to offline course-content. 3. Impact of implementing this LMS platform in the teaching and learning process is not yet included on this phase of research |
| futurwork | This study has several spaces for further improvements: 1. Other attributes such as students’ attendance, economic status and interests might be included, as well as possible predictors in determining the performance of students in Java programming. 2. Numerical value of students’ final grade might be considered to provide a more specific and personal prediction better than the “Passed” or “Failed” remarks. 3. Combination of multiple algorithm in classifying data set is also recommended to further improve the algorithm and rule sets of prediction |
| conclusion | The existing frameworks for LMS found in recent literatures and studies can still be improved by applying the concept of educational data mining and recommendation systems. LMS features can go beyond having traditional functionalities for the management of learning materials, courses, student records, and the like. Data mining can be explored to develop feature which can classify students according to their predicted performance. Although a data mining task is a multi-stage process and may take a long time, the benefit and value that it can add to a learning management system is worth all the challenges. Integrating a prediction system, which considers students grades in previous relatedsubjects, is a great aid to the teachers in conducting a pre-assessment of students’ possible performance in the future. A module which can recommends applicable course-content with consideration to the learners’ index of learning style, adds power to the functionality of the LMS. Aside from the usual way of simply recommending learning topics, recommendations on how the learner could make the most out of the learning experience are also provided. The framework of this study is a good attempt at improving the current state of LMS technology. There are still many challenges that should be examined to come up with a perfect virtual learning system or personalized learning environment that can really satisfy all the needs and uniqueness of each learner |
| dataR | 08-May-20 |

### T27-17 Title : In-Depth Analysis of the Felder-Silverman Learning Style Dimensions

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| --- | --- |
| **subject** | **description** |
| serial | 17 |
| title | In-Depth Analysis of the Felder-Silverman Learning Style Dimensions |
| year | 2007 |
| abstract | Learning styles are increasingly being incorporated into technology-enhanced learning.  Appropriately, a great deal of recent research work is occurring in this area. As more information  and details about learning styles becomes available, learning styles can be better accommodated and integrated into all aspects of educational technology. The aim of this paper is to analyse data about learning styles with respect to the Felder-Silverman learning style model (FSLSM) in order to provide a more detailed description of learning style dimensions. The analyses show the most representative characteristics of each learning style dimension as well as how representative these characteristics are. As a result, we provide additional information about the learning style dimensions of FSLSM. This information is especially important when learning styles are incorporated in technology-enhanced learning. |
| keywords | learning styles, Felder-Silverman model, data mining, student modelling. |
| purpose | aim at identifying characteristics of each of the four dimensions of FSLSM in order to be able to make a more gradual distinction within the learning style dimensions. Furthermore, we analyse how representative each characteristic is for each learning style dimension. |
| conclusion | Especially for the use of learning styles in technology-enhanced learning, such an accurate description is important for relating the learning style model with the features of the online environment. In recent years, technology-enhanced learning has put great attention on learning styles in order to improve adaptivity in technology-enhanced educational systems. Incorporating not only learning style dimensions but also the different characteristics within these dimensions lead to a more accurate representation of students’ learning styles and therefore enhance the potentials of adaptive learning environments. Moreover, the in-depth investigation of  learning style characteristics could improve also pedagogical models, supporting a more effective and personalized learning |
| futurework | Future work will include additional statistical analyses in order to confirm our results. An extension of the results of the ILS questionnaire might be a meaningful aim for future work as well, in order to provide not only information about the learning style dimension but also about their semantic groups. Furthermore, we plan to use the additional information of semantic groups for improving student modelling and use this additional data in the student model to provide more suitable adaptivity. Another area of application and future research work will deal with incorporating the detailed description of learning styles to detect learning styles automatically from the behaviour of students in online courses. Moreover, the more detailed information can help to investigate relationships between learning styles and, for instance, performance or characteristics of students such as cognitive traits |
| dataR | 08-May-20 |

### T28-18 Title : Factors affecting students completion : study of online Masters Program

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| --- | --- |
| **subject** | **description** |
| serial | 18 |
| year | 2015 |
| title | Factors affecting students completion : study of online Masters Program |
| area | LS |

### T29-19 Title : EDM & students performance prediction

|  |  |
| --- | --- |
| **subject** | **description** |
| area | EDM |
| title | EDM & students performance prediction |
| year | 2016 |
| serial | 19 |

### T30-20 Title : Use of Felder and Silverman learning style model for online course design

|  |  |
| --- | --- |
| **subject** | **description** |
| serial | 20 |
| title | Use of Felder and Silverman learning style model for online course design |
| link1 | <https://www.researchgate.net/publication/328711554_Use_of_Felder_and_Silverman_learning_style_model_for_online_course_design> |
| year | 2018 |
| abstract | Learning Management Systems are used in millions of higher education courses, across various countries and disciplines. Teachers build courses reflecting their individual teaching methods, which may not always fit students’ different learning styles. However, limited information is known about how well these courses support the learners. The study aims to explore the use of Felder and Silverman learning style for online course design. The study has used linear transfer function system models to develop fundamentals of feedback by a course analyzer tool. This interactive tool allows teachers to determine a course’s support level for specific learning styles, based on the Felder and Silverman learning style model. The Felder and Silverman learning style model in this study is used to visualize the fit between course and learning style to help teachers improve their course’s support for diverse learning styles. The results of a pilot study successfully validated the course analyzer tool, as it has potential to improve the design of the course in future and allow more insight into overall student performance. The findings suggest that a course designed with certain learning styles in mind can improve learning of the students with those specific learning styles. |
| authors | Moushir M. El‑Bishouty1,7 · Ahmed Aldraiweesh2 · Uthman Alturki2 · Richard Tortorella3 · Junfeng Yang4 · Ting‑Wen Chang5 · Sabine Graf1 · Kinshuk |
| keywords | Course analysis; Course design ; Learning management system ; Learning style ; Online education |
| purpose | Limited attention has been paid on how to support teachers, who wish to adapt their courses to specific learning styles. Thus, this study has presented an interactive tool designed for the analysis of exist-ing course content in LMSs. Moreover, the effectiveness of a tool or methodology can be measured based on the feedback of the students. Additionally, the teaching methodology or tool must align with the needs of the students. Moreover, pilot study has been conducted to validate the efficacy of the tool and investigate ways of improvement. |
| RO | Identifying students’ learning styles and adapting courses |
| method | Tool is used by teachers to examine whether the students are comfortable with the tool or not. Furthermore, the instructors are able to design the curriculum in an effec-tive manner, so that the students can easily understand the teaching material. The linear transfer function system models are used for developing fundamentals of feedback by the course analyzer. |
| RQ | Q1: Will the current course analyzer tool help teachers to develop more robust teaching strategies based on learning styles?  Q2: How can the proposed tool be implemented in class lectures and group discussions? Q3: Is the proposed course analyzer tool reliable in terms of the challenges faced by teachers in their teaching methods |
| comments | Learning objects have a direct impact on the selection of learning style. |
| conclusion | study has demonstrated the validity of the course analyzer tool at the cohort level and shed light on how the course can be improved. The tool can be helpful for teachers in evaluating the preference of students regarding a particular course, to this end, the teaching methodology can be significantly improved leading to better students’ assess-ment outcomes. |
| highlights | The implications of having such a tool are numer-ous, with the ability to determine specific strengths and weaknesses of a course from the pedagogical standpoint. It is also believed that teachers will be able to use this tool to make changes not only post hoc but also during the course itself |
| dateR | 08-May-20 |

### T31-21 Title : Discovering Students use of Learning Resources with EDM

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| --- | --- |
| **subject** | **description** |
| serial | 21 |
| year | 2016 |
| title | Discovering Students use of Learning Resources with EDM |
| area | LA |

### T32-22 Title : Framework for LA in Moodle for assessing Course Outcomes

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| --- | --- |
| **subject** | **description** |
| serial | 22 |
| year | 2016 |
| title | Framework for LA in Moodle for assessing Course Outcomes |
| area | LA |

### T33-23 Title : Predicting Grades

|  |  |
| --- | --- |
| **subject** | **description** |
| serial | 23 |
| year | 2016 |
| area | LA |
| title | Predicting Grades |

### T34-24 Title : EDM & students performance prediction

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| --- | --- |
| **subject** | **description** |
| serial | 24 |
| year | 2016 |
| title | EDM & students performance prediction |
| area | LA |
| notes | Maybe duplicate |

### T35-25 Title: Finding Key Integer Values in Many Features for Learners Academic Performance Prediction

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| --- | --- |
| **subject** | **description** |
| serial | 25 |
| year | 2017 |
| title | Finding Key Integer Values in Many Features for Learners Academic Performance Prediction |
| area | LA |

### T36-26 Title : Predicting Students performance based on Learning Style byu using ANN

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| --- | --- |
| **subject** | **description** |
| serial | 26 |
| year | 2017 |
| title | Predicting Students performance based on Learning Style byu using ANN |
| area | LA |

### T37-27 Title : Using Learning Analytics to Predict Students Performance in Moodle LMS : Case of Mbeya University of Science & Technology

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| --- | --- |
| **subject** | **description** |
| serial | 27 |
| year | 2017 |
| title | Using Learning Analytics to Predict Students Performance in Moodle LMS : Case of Mbeya University of Science & Technology |
| area | LA |
| link1 | <https://onlinelibrary.wiley.com/doi/abs/10.1002/j.1681-4835.2017.tb00577.x> |
| abstract | The past decade has seen the rapid adoption and use of various Learning Management Systems (LMS) in Africa, and Tanzania in particular. Institutions have been spending thousands of dollars to implement these systems in a bid to improve the quality of education as well as increasing students’ enrolments through distance and blended learning. However, the impact of these system on improving students’ performance has been a popular subject of research in recent years. Studies have been relying on data from users’ opinions and subjective interpretation through surveys to determine the effectiveness of LMS usage on students’ learning performance. The use of such data is normally subject to the possibility of distortion or low reliability. Therefore, this study designed and developed a Learning Analytics tool and used the tool to determine the causation between LMS usage and students’ performance. Data from LMS log of two courses delivered at Mbeya University of Science and Technology (MUST) were extracted using developed Learning Analytics tool and subjected into linear regression analysis with students’ final results. The study found that discussion posts, peer interaction, and exercises were determined to be significant factors for students’ academic achievement in blended learning at MUST. Nonetheless, time spend in the LMS, number of downloads, and login frequency were found to have no significant impact on students’ learning performance. The implications of these results on improving students’ learning are discussed. |
| keywords | Learning analytics, Educational Technology, LMS, Higher education, eLearning |
| results | time spent in the LMS, number of downloads, and login frequency were found to have no significant impact on students’ learning performance. discussion posts, peer interaction, and exercises were determined to be significant factors for students’ academic achievement in blended learning at MUST |
| techniques | linear regression analysis with students’ final results |
| data | Data from LMS log of two courses delivered at Mbeya University of Science and Technology (MUST) were extracted using developed Learning Analytics tool |
| conclusion | The results generally imply that **students who obtained better grades were those who were active in the discussion forums and interacted more with peer students.** Moreover, **students who completed exercises obtained better grades compared to those who did not.** Several studies have determined that a strong relationship exists between students’ LMS usage and academic performance. Our findings on the causation between students’ activities in the LMS and students’ final grades is in line with experiences and results from the literature. |
| purpose | The study was conducted at MUST with two courses having a total of 171 students. |
| RQ | The LA system developed had impact on students performance in LMS |
| RO | Design and Develop LA tool and use it to determine causation between LMS usage & students learning performance |
| method | variables were solicited from the literature that were used to design and develop the Learning Analytics tool. The developed tool was used to extract data from two courses namely Analysis for Applied Biology and Service and Installation IIT offered in blended mode at MUST in the academic year 2004/2015. Data obtained from LMS usage via the Learning Analytics tool was then subject to linear regression in order to determine the effect of LMS usage on students’ performance. |
| results | study found that **Peer Interaction (beta value=19.6%), and Forum Posts (beta value=77.1%)** had significant effect on students’ performance on Applied Biology course while **Forum Posts (beta value=48.5%), and Exercise (beta value=51.5%)** had an impact on students’ performance on Service and Installation IIT course. Forum Posts has shown to have significant effect on students’ learning performance in both courses. This means, students who were active in the discussion forums during course delivery performed better that those who were less active. These findings imply that MUST should find strategies that will increase students’ participation in discussion forums in order to increase students’ performance. This can be done by grading quality and quantity students’ posts in discussion forums.  **Peer Interaction** had impact on students’ performance in Analysis for Applied Biology course. This finding in accord with recent studies which found that student-student interaction had a significant impact on students’ academic performance (Agudo-Peregrina et al., 2012; Yu & Jo, 2014). This implies that, institutions should promote for peer interactions amongst students in in order to increase students’ performance in courses offered via the LMS.  **Exercises** was found to be the contributing factor in students’ final scores in the Service and Installation II course. The result implies that instructors at MUST should consider giving their students more exercises in order to improve their final scores. This finding is similar to a study conducted by Dietz-Uhler and Hurn (2013) who found that the performance on course assignments predicted students’ final grades in an online course |
| comments | finding seems to be consistent with studies conducted elsewhere LMS forums posts had impact on students’ final grade. For instance, participation frequency in online activities was significantly associated with their grades in a study conducted at University of Glamorgan, UK with 122 students (Davies & Graff, 2005). Similar findings were obtained in studies conducted in various institutions (e.g. Agudo-Peregrina et al., 2012; Beer et al., 2010). |
| highlights | study has shown that LMS usage have impact in students’ performance in courses offered via LMS. Surprisingly, number of downloads, login frequency, time spend in the LMS were found to have no significant impact on students’ performance in both courses. |
| limitations | The study was based on quantitative results obtained using data stored in LMS database. However, logs simply record learners’ behavior in LMS, but they do not explain why some of the factors were significant and some were not significant. Further research **should be undertaken to determine why other factors were significant while others were not using qualitative research design**. This can be done by conducting interviews or focus group discussions with students who were using the LMS or with instructors who used the LMS to facilitate these courses  two courses used in this study were not delivered entirely online. They were delivered in blended mode with some face-to-face activities taking place. As a result, there are many offline activities such as reading course-related books, lectures, and offline students’ peer interactions could not tracked in the LMS. To **develop a full picture of the LMS features and activities that contributed towards students’ performance future studies should select courses that are offered entirely online via the LMS.**  the study examined only two courses in one academic year 2014/2015. Further research could expand to many courses that are offered in a given semester or for selected courses offered in some semesters. |
| futurework | Purely only LMS; Investigate why other factors were not significant (forum/ questionnaire) |
| myres | Survey to find why Downloads & other variable are not significant; how can unused activities be maximised |
| comments | Learning Analytics tools can be used to analyze how students use LMS and find ways find strategies that can be used to maximize LMS usage. The majority of LMS adopted in higher education in Africa tend to fail partially or totally (Ssekakubo et al., 2011) due to the fact that relatively few features are normally used. The use of Learning Analytics tool can be used to identify unused features and in turn, institutions can find ways of maximizing usage. |
| rating | 7 |

### T38-28 Title : Educational DM & Data Analysis for optimal Learning Content Management

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| --- | --- |
| **subject** | **description** |
| serial | 28 |
| year | 2017 |
| futurework | Clustering of learning material, optimal sequence |
| methods | Clustering, Linear Regression |
| factors | Counts of scrolls, time between events & various assessment scores, per session test |
| title | Educational DM & Data Analysis for optimal Learning Content Management |
| area | LA |
| results | TBA / Session Lengths follow Log normal & exponential distributions |
| RO | Time Between Actions (TBA) |
| RQ | Whether TBA follows any PDF & if so which one. Whether paramters of such PDF serve as features for the clustering |
| link1 |  |
| data |  |
| authors |  |

### T39-29 Title : EDM & Learning Analysis

|  |  |
| --- | --- |
| **subject** | **description** |
| serial | 29 |
| year | 2017 |
| methods | Clustering |
| title | EDM & Learning Analysis |
| area | LA |
| data | log |
| factors | Time Spent, Time Taken Time Forum, Days Theory, Word in Forum, Sentence in Forum |

### T40-30 Title : Review of EDM Techniques & Recommendation model in analysing Student performance

|  |  |
| --- | --- |
| **subject** | **description** |
| serial | 30 |
| year | 2017 |
| area | LA |
| title | Review of EDM Techniques & Recommendation model in analysing Student performance |

### T41-31 Title : A survey of EDM research

|  |  |
| --- | --- |
| **subject** | **description** |
| serial | 31 |
| year | 2017 |
| area | LA |
| title | A survey of EDM research |

### T41-32 Title : A LA approach for student performance assessment

|  |  |
| --- | --- |
| **subject** | **description** |
| serial | 32 |
| year | 2018 |
| area | LA |
| title | A LA approach for student performance assessment |

### T43-33 Title: A literature review of empirical research on learning analytics in medical education

|  |  |
| --- | --- |
| **subject** | **description** |
| serial | 33 |
| year | 2018 |
| area | LA |
| title | A literature review of empirical research on learning analytics in medical education |

### T44-34 Title : Using Learning Analytics to Predict (and Improve) Student Success: A Faculty Perspective

|  |  |
| --- | --- |
| subject | description |
| serial | 34 |
| link1 | <https://www.researchgate.net/publication/286878239_Using_learning_analytics_to_predict_and_improve_student_success_A_faculty_perspective> |
| title | Using learning analytics to predict (and improve) student success: A faculty perspective |
| dataR | 09-May-20 |
| abstract | Learning analytics is receiving increased attention, in part because it offers to assist educational institutions in increasing student retention, improving student success, and easing the burden of accountability. Although these large-scale issues are worthy of consideration, faculty might also be interested in how they can use learning analytics in their own courses to help their students succeed. In this paper, we define learning analytics, how it has been used in educational institutions, what learning analytics tools are available, and how faculty can make use of data in their courses to monitor and predict student performance. Finally, we discuss several issues and concerns with the use of learning analytics in higher education. |
| conclusion | It seems clear that learning analytics is gaining momentum and is likely here to stay (e.g., Horizon Report, 2012). There are many benefits to learning analytics; most notably that it can inform how we help our students succeed. In educational institutions, we have an enormous amount of data at our disposal. Our ability to harness this data and use it to inform what we do in the classroom, whether face-to-face or online, is at the heart of learning analytics. Institutions such as Purdue University, Rio Salado Community College, and University of Michigan are blazing the trail and demonstrating the vast benefits of learning analytics for students and faculty. But, as studies have indicated (e.g., Abdous, He, & Yen, 2012; Dietz-Uhler & Hurn, 2012; Falakmasir & Jafar, 2010; Minaei-Bidgoli, Kashy, Kortemeyer, & Punch, 2003), individual faculty can make use of the data they have available in their courses to affect change and improve student success. These efforts, although seemingly “small-scale”, can have a large impact on student success. |
| publication | January 2013 Journal of Interactive Online Learning 12(1):17-26 |
| year | 2013 |
| ISSN | EISSN-1541-4914 |
| rating | 6 |
| results | In a recent study, Dietz-Uhler, Hurn, and Hurn (2012) found that performance on course  assignments and tests at various times in the course significantly predicted final grades in an  online introductory psychology class. Specifically, they found that performance on the first two  exams, a quiz on the syllabus taken before the class started, and assignments in the second half of the course accounted for 98% of the variance in final course grades. With regard to data generated from an LMS, the only variable that significantly predicted final course grade was the number of discussion board posts authored in the second half of the course. These results **suggest that it is important to examine performance and behavior indicators at various points in the course in order to help students perform better in the course** |
| myres | Examine Performance and Behaviour indicators at various points in the course |

### T45-35 Title : Can we Predict Student Learning Performance from LMS Data ? A Classification approach

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| --- | --- |
| **subject** | **description** |
| serial | 35 |
| year | 2018 |
| title | Can we Predict Student Learning Performance from LMS Data ? A Classification approach |
| area | EDM |
| tags | LMS, Predict, Classification |
| link1 | <https://www.computer.org/csdl/journal/lt/2017/01/07589022/13rRUwI5TZp> |
| link2 | <https://www.researchgate.net/publication/334130244_Can_We_Predict_Student_Learning_Performance_from_LMS_Data_A_Classification_Approach> |
| DOI | 10.2991/iccie-18.2019.5 |
| abstract | The Learning Management System (LMS) is a common occurrence in most educational institutions. This system is a software application helping the educator in administration, facilitation, and tracking, of course content to the learner. Educators have always been interested in understanding student interaction with systems like LMS. Such a system generates a plethora of data in a variety of form such as student performance on the individual course, activities, student behaviours, etc. The most prominent solutions involve performing dimensionality reduction technique to improve classifier accuracy and reducing the fewer error rates. Therefore, this study utilizes feature selection as a dimensionality reduction technique. The multiclass data were handled using the Learning Vector Quantization (LVQ) algorithm to identify significant predictors and thereby reducing the biased result. The efficiency of feature selection technique is evaluated with five different classifiers such as Linear Discriminant Analysis (LDA), Classification and Regression Tree (CART), k-Nearest Neighbor (KNN), Support Vector Machine (SVM), and Random Forest (RF). The performance of the classifier is evaluated using the kappa statistics and confusion matrix. Our extensive experimental results show that RF classifier produces optimum kappa statistic (85 %) with LVQ. |
| keywords | Predictive Models, Analytical Models, Data Models, Frequency Measurement, Learning Management Systems, Internet, Student Performance, Learning Analytics, Learning Management Systems, Portability, Predictive Modeling |
| results | results of predictive modeling, notwithstanding the fact that they are collected within a single institution, strongly vary across courses. Thus, the portability of the prediction models across courses is low. In addition, we show that for the purpose of early intervention or when in-between assessment grades are taken into account, LMS data are of little (additional) value |
| myres | Here it is said that Early Intervention / in -between assessment grades are of little value (contradictory to other papers) |
| notes | Much research in the field of learning analytics has used LMS data for predictive modeling of student performance to predict students’ grades and to predict which students are at risk of failing a course [6], [7], [8]. This is an important step in learning analytics, as it informs the implementation of interventions, such as personalized feedback.  Studies predicting student success in offline education have typically collected measurements using validated questionnaires, interviews, and observational techniques, with relevant theoretical concepts in mind so that the measurement can be geared towards the concepts that the researcher thinks need to be measured. The use of LMSs allows for tracing and analyzing students’ online behavior without the necessity of time-consuming data-collection. However, LMSs provide raw log data that are not concrete measurements of previously outlined theoretical concepts. It is therefore important to understand whether and how these data can be used for learning analytics. Recent studies show a wide variety in the analytical usage of LMS data: different kinds of analytical methods and predictors are used, often without explicit mention of the theoretical argumentation behind them [9]. Moreover, many studies analyze LMS data of one or a few institutions, for one or only a few courses, or describe special cases (e.g., courses using tailor-made e-tutorial packages). This makes it hard to compare the different studies and draw general conclusions about the ways in which to use LMS data for predictive modeling. |
| RQ | whether there actually is a single best way to predict student performance across a diverse set of courses. |
| points | Studies that have used similar methods and predictors have nonetheless found different results in the correlational analyses and prediction models. Even within one institution using the same LMS, differences have been found in the prediction models of nine blended courses [10]. Thus, the effects of LMS behavior on student performance might differ per institution or even per course |
| highlights | a study using 29 courses (204 offerings, 352 unique students), has found that the variance in students’ performance (final grade), was accounted for by individual differences (18 percent) as well as course offerings (22 percent) [11]. Hence, the so-called “portability” of prediction models across courses might not be that high, even though it might still be that prediction models can be successfully used in single courses.  most studies focus on predicting student performance after a course has finished, establishing how well student performance could have been predicted with LMS usage data, but at a point in time where the findings cannot be used for timely intervention anymore [12]. As LMS data provide information during the whole course, it seems useful to determine whether data from only the first weeks of a course are enough for accurate prediction of student performance |
| tags | Portability of Model, LMS, Prediction |
| futurework | Portabillity |

### T46-36 Title : Data mining in course management systems: Moodle case study and tutorial

|  |  |
| --- | --- |
| subject | description |
| serial | 36 |
| year | 2018 |
| title | Data mining in course management systems: Moodle case study and tutorial |
| link1 | <https://www.academia.edu/2400757/Data_mining_in_course_management_systems_Moodle_case_study_and_tutorial> |
| area | PM |
| tags | Moodle, Data Mining |

### T47-37 Title : xxxxx

|  |  |
| --- | --- |
| **subject** | **description** |
| serial | 37 |
| year |  |
| area | LA |

### T48-38 Title : Student Engagement Predictions in an e-Learning Systems and their Impact on Student Course Assessment Scores

|  |  |
| --- | --- |
| **subject** | **description** |
| serial | 38 |
| year | 2018 |
| area | LA |
| title | Student Engagement Predictions in an e-Learning Systems and their Impact on Student Course Assessment Scores |

### T49-39 Title : xxxxxx

|  |  |
| --- | --- |
| **subject** | **description** |
| serial | 39 |
| area | LA |

### T50-40 Title : xxxxxx

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| --- | --- |
| **subject** | **description** |
| serial | 40 |
| area | LA |

### T51-41 Title : LA Challenges : Trade-offs, Methodology, Scalability

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| --- | --- |
| **subject** | **description** |
| serial | 41 |
| year | 2020 |
| area | LA |
| title | LA Challenges : Trade-offs, Methodology, Scalability |

### T52-42 Title : Prediction of student academic performance using Moodle Data from a Further Education setting

|  |  |
| --- | --- |
| **subject** | **description** |
| serial | 42 |
| year | 2020 |
| area | LA |
| title | Prediction of student academic performance using Moodle Data from a Further Education setting |
| tags | Moodle, Performance, Prediction |

### T53-43 Title : Analysing Performance of Students by using DM techniques (LR)

|  |  |
| --- | --- |
| **subject** | **description** |
| serial | 43 |
| year |  |
| area | LA |
| title | Analysing Performance of Students by using DM techniques (LR) |
| tags | Performance, Students, DM |

### T54-44 Title: Comparing the factors that predict completion & grades among for Credit & open/ MOOC students in online learning

|  |  |
| --- | --- |
| **subject** | **description** |
| serial | 44 |
| year |  |
| area | LA |
| title | Comparing the factors that predict completion & grades among for Credit & open/ MOOC students in online learning |
| tags | Factors, Prediction, Grades, MOOC |

### T55-45 Title: Comparison of 17 Blended Courses using Moodle LMS

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| --- | --- |
| **subject** | **description** |
| serial | 45 |
| year | 2017 |
| area | LA |
| title | Comparison of 17 Blended Courses using Moodle LMS |
| tags | Courses, Moodle, LMS, Comparison |
| link1 | <https://ieeexplore.ieee.org/document/7589022> |
| citations | 54 |
| abstract | With the adoption of Learning Management Systems (LMSs) in educational institutions, a lot of data has become available describing students' online behavior. Many researchers have used these data to predict student performance. This has led to a rather diverse set of findings, possibly related to the diversity in courses and predictor variables extracted from the LMS, which makes it hard to draw general conclusions about the mechanisms underlying student performance. We first provide an overview of the theoretical arguments used in learning analytics research and the typical predictors that have been used in recent studies. We then analyze 17 blended courses with 4,989 students in a single institution using Moodle LMS, in which we predict student performance from LMS predictor variables as used in the literature and from in-between assessment grades, using both multi-level and standard regressions. Our analyses show that the results of predictive modeling, notwithstanding the fact that they are collected within a single institution, strongly vary across courses. Thus, the portability of the prediction models across courses is low. In addition, we show that for the purpose of early intervention or when in-between assessment grades are taken into account, LMS data are of little (additional) value. We outline the implications of our findings and emphasize the need to include more specific theoretical argumentation and additional data sources other than just the LMS data. |
| DOI | 10.1109/TLT.2016.2616312 |
| ISSN | 1939-1382 |
| publication | IEEE Transactions on Learning Technologies ( Volume: 10 , Issue: 1 , Jan.-March 1 2017 ) |
| keywords | Predictive models, Analytical models, Data models, Frequency measurement, Learning management systems, Internet |
| results | predictor variables did not correlate significantly for all courses, and some of the variables showed significant and substantial differences in effect sizes and even the direction of the correlation across courses. This suggests that the effects of these variables as predictors in a multivariate analysis may also differ across courses. |
| purpose | Predict Student performance from LMS predictor variables as used in literature and from in-between assessment grades, using both multi-level and standard regressions |
| RQ | Is there a single best way to predict students performance across a diverse set of course ? |
| RO | Do results when predictive modeling is used from different courses vary ? |
| conclusion | results of predictive modeling, notwithstanding the fact that they are collected within a single institution, strongly vary across courses. Thus, the portability of the prediction models across courses is low. |
| myres | Cannot apply one prediction model developed in one course to other courses **(No Portability)**  **No general conclusions about mechanisms underlying student performance can be drawn** |
| limitations | A limitation of this study is that data was available for only a part of the courses provided by the university, resulting in a skewed representation of courses: mostly first year courses with similar use of blended learning. Thus, our results might not carry over to other types of courses or blended learning. However, given the similarity of our courses, one would argue that portability of the results would be more likely, which we nevertheless do not find. |
| futurework | It may be useful to further investigate the effect of specific course and module characteristics, for example based on the course syllabi, on the use of the LMS (cf. [11]). Unfortunately, inconsistencies across course findings make it difficult to draw general conclusions about the online behavior of potential students at risk. Additional theoretical argumentation and data sources need to be included to predict student performance and improve learning and teaching. |
| comments | In our case, we could only investigate 17 courses, which does not allow for a lot of variation within course modules. Another potential issue with this explanation is that these post-hoc analyses suggest that the larger amount of the variation seemed to reside at the student level. potential inclusion of more detailed course characteristics, it may also be useful to consider that students differ in how they use LMSs while studying. Our multi-level analyses indeed show that a high proportion of variance could be explained at the student level. This is promising, in the sense that it does appear to be variation in student characteristics or usage level that can accurately predict the final exam grade. On the other hand, none of the usage characteristics that have been used in the literature before (most of which we included here) seemed to pick up this variance. |
| gaps | As their study was conducted on a heterogeneous set of students from only two courses, and as previous studies have shown to be quite diverse, future work is needed to draw conclusions about the usage of learning dispositions combined with LMS data for early feedback. Currently, we are supplementing our data with such other data sources. |
| rating | 9 |

### T56-46 Title : Detecting Learning Styles in Learning Management Systems Using Data Mining

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| --- | --- |
| **subject** | **description** |
| serial | 46 |
| year | 2016 |
| area | LS |
| title | Detecting Learning Styles in Learning Management Systems Using Data Mining |
| tags | Learning Styles |
| link1 | <https://www.jstage.jst.go.jp/article/ipsjjip/24/4/24_740/_pdf> |
| dataR | 08-May-20 |
| abstract | The use of data mining in the education sector has increased in the recent past. One reason for this is the wide use of learning management systems (LMS), which store data related to learning activities. The goal of this research is to predict individual learning styles using the Moodle LMS by analyzing log data using a data mining technique. We use the Waikato environment for knowledge analysis (Weka), as the data mining tool and compare the differences in the performance of several data mining techniques using course log data. Our experimental results show that the J48 decision tree classification algorithm works best with our dataset. We also propose a group learning map that visualizes the learning styles in a class, which can help instructors and learners achieve learning outcomes more effectively. |
| DOI | 10.2197/ipsjjip.24.740 |
| publication | Journal of Information Processing 24(4):740-749 |
| keywords | learning management systems, learning styles, moodle, data mining |
| results | J48 decision tree classification algorithm works best with our dataset. |
| purpose | predict individual learning styles using the Moodle LMS by analyzing log data using a data mining technique |
| RQ |  |
| RO | Automate the process of learning style extraction from Moodle LMS using DM technique |
| comments | learning style classification mod-els, the Felder-Silverman learning style model (FSLSM) hasbeen recognized and applied to e-learning environments. important factor to consider is that an individual learning style may vary because of many factors within the course or LMS. For example, different course content, subjects, threshold data for the course, and learne behavior and experience of online learning may affect an individ-ual’s learning style. Thus, such systems must be able to respond dynamically to such divergence  FSLSM is the learning style model that is mostfrequently cited with respect to computer-based education sys-tems [7], [8], [9], [10], [11], [12], [13], [14], [17], [18], [19] |
| limitations | Only 1 course considered. Learner preference may vary for each course due to differing subject matter and type of learning material (videos,text) ; Learner experience with online learning can affect the interaction with LMS. Selection of Algorithms . Depending upon type of course resources and student performance, prediction accuracies may vary. |
| scope | Course with 80 students at HE institute |
| techniques | J48, Bayesian network, Naive Bayes, Random Forests to predict Learning Styles |
| conclusion | Better performance, New feature to visualise and analyse learning styles. Can be used by leaers and instructors alike |
| futurework | Consider undesirable behaviours such as non genuine users (cheating). Customise content provided to each learner based on their learning style.  Further testing with different courses is required to obtain a clearer understanding |

### T57-47 Title : E-learning : Challenges & Research opportunities using ML & Data Analytics

|  |  |
| --- | --- |
| **subject** | **description** |
| serial | 47 |
| year |  |
| area | LA |
| title | E-learning : Challenges & Research opportunities using ML & Data Analytics |
| tags | Elearning, Machine Learning, Data Analytics, Research, Challenges |

## 

### T58-48 Title : EDM & data analysis for optimal learning content management

|  |  |
| --- | --- |
| **subject** | **description** |
| serial | 48 |
| year |  |
| area | LA |
| title | EDM & data analysis for optimal learning content management |
| tags | EDM, Data Analysis, Learning, Content |

### T59-49 Title : xxxxx

|  |  |
| --- | --- |
| **subject** | **description** |
| serial | 49 |
| year |  |
| area | LA |

### T60-50 Title : Intelligence & affect as predictors of Academic Performance among UG students

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| --- | --- |
| **subject** | **description** |
| serial | 50 |
| year |  |
| area | LA |
| title | Intelligence & affect as predictors of Academic Performance among UG students |
| link1 |  |

### T61-51 Title : LA in a smart classroom to improve eEducation

|  |  |
| --- | --- |
| **subject** | **description** |
| serial | 51 |
| year |  |
| area | LA |
| title | LA in a smart classroom to improve eEducation |
| tags | LA, Smart Classroom, eEducation |

### T62-52 Title : Machine Learning Based Student Grade Prediction : Case Study

|  |  |
| --- | --- |
| **subject** | **description** |
| serial | 52 |
| year |  |
| area | LA |
| title | Machine Learning Based Student Grade Prediction : Case Study |
| tags | Machine Learning, Student, Grade, Prediction, Case Study |

### T63-53 Title: ML application in MOOCs : Dropout prediction

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| --- | --- |
| **subject** | **description** |
| serial | 53 |
| year |  |
| area | LA |
| title | ML application in MOOCs : Dropout prediction |
| link1 |  |

### T64-54 Title : ML approaches to predict learning outcomes in Massive Open Learning Courses

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| --- | --- |
| **subject** | **description** |
| serial | 54 |
| year |  |
| area | LA |
| title | ML approaches to predict learning outcomes in Massive Open Learning Courses |
| link1 |  |

### T65-55 Title : Open Student Models of Core Competencies at the Curriculum level : Using LA for Student retention

|  |  |
| --- | --- |
| **subject** | **description** |
| serial | 55 |
| year |  |
| area | LA |
| title | Open Student Models of Core Competencies at the Curriculum level : Using LA for Student retention |
| link1 |  |
| tags | Student, LA |

### T66-56 Title: Personalised Multi-Regression Models for Predicting students performance in Course Activities

|  |  |
| --- | --- |
| **subject** | **description** |
| serial | 56 |
| year |  |
| area | LA |
| title | Personalised Multi-Regression Models for Predicting students performance in Course Activities |
| link1 |  |
| tags | Regression, Models, Student, Performance, Course |

### T67-57 Title : Predicting STEMP achievement with LMS data : Prediction modeling and a Test of an Early Warning System

|  |  |
| --- | --- |
| **subject** | **description** |
| serial | 57 |
| year |  |
| area | LA |
| title | Predicting STEMP achievement with LMS data : Prediction modeling and a Test of an Early Warning System |
| tags | LMS, Prediction |

### T68-58 Title : Predicting Students Performance using Advance Learning Analytics

|  |  |
| --- | --- |
| **subject** | **description** |
| serial | 58 |
| year |  |
| area | LA |
| title | Predicting Students Performance using Advance Learning Analytics |
| link1 |  |
| tags | LA, Student, Performance |

### T69-59 Title: When LA meets E-Learning

|  |  |
| --- | --- |
| **subject** | **description** |
| serial | 59 |
| year |  |
| area | LA |
| title | When LA meets E-Learning |
| link1 |  |
| tags | LA, ELearning |

### T70-60 Title : What is LA about ? A Survey of Different Methods used in 2013-15

|  |  |
| --- | --- |
| **subject** | **description** |
| serial | 60 |
| year |  |
| area | LA |
| title | What is LA about ? A Survey of Different Methods used in 2013-15 |
| link1 |  |
| tags | LA, Methods |

### T71-61 Title : Potential of LA & Big Data

|  |  |
| --- | --- |
| **subject** | **description** |
| serial | 61 |
| year |  |
| area | LA |
| title | Potential of LA & Big Data |
| tags | Learning Analytics, Big Data |

### T72-62 Title : Educational Data Mining: An Application of Data Mining To Estimate Students’ Performance

|  |  |
| --- | --- |
| **subject** | description |
| **serial** | 62 |
| **title** | Educational Data Mining: An Application of Data Mining To Estimate Students’ Performance |
| **area** | LA |
| **authors** | Rima Anant kumar Patel, Bhavika Patel, Dweepna Garg, Binal Kaka |
| **year** | 2020 |
| **publication** | Aut Aut Research Journal |
| **results** |  |
| **conclusion** | presented various methods that can be used in educational data mining.  Discussed the issues that can be faced in data mining. Through the educational data mining we can measure the performance of the student in the context of different subjects. Different models can be used to perform the different data mining techniques. Focus of the paper is on to estimate the performance of the student, their learning behaviour and to detect the outlier in order to improve the result of an individual. This kind of techniques can be use to improve the overall result in educational  organization at high level also |
| **futurework** | future educational data mining can be applied to improve the  teaching-learning methods. It will play vital role in the overall performance of teaching professionals. In future, we can generate the model from which students’ performance can be measured based on the subject dependency. If student is good in some subject then we can predict the  skills of the student in other subject also. For this purpose clustering, classification and prediction techniques can be used |
| **gaps** |  |
| **abstract** | Data Mining is most commonly used technique which is used to extract the data from the different sources and organize them into meaningful information. In the current age and day, data plays a vital role. Data mining is the process of collection, cleaning and organization of raw data into useful information. Though widely used in all of the sectors either business based or government, it still suffers with the some of the issues that needs to be addressed and solved. With rapid evolution in the field of data  mining, companies are expected to stay on line with all the new developments. In this paper we have enlighten the current trends and  issues along with the future trends in data mining |
| **chapters** | INTRODUCTION, RELATED WORK, CURRENT ISSUES FACED IN DATA MINING, METHODS OF EDUCATIONAL DATA MINING, APPLICATION OF DATA MINING, RESULT ANALYSIS |
| **dateR** | 22-Apr-2020 |
| **dateA** | 22-Apr-2020 |
| **links** | <http://autrj.com/gallery/13-aut-april-4071.pdf> |
| **tags** | EDM, Performance |

### T73-63 - Using data mining on student behavior and cognitive style data for improving e-learning systems: A case study

|  |  |
| --- | --- |
| subject | description |
| serial | 63 |
| title | Using data mining on student behavior and cognitive style data for improving e-learning systems: A case study |
| authors | Jovanovic, Vukicevic, Milovanovic, and Minovic |
| link1 | <https://www.researchgate.net/publication/261581685_Using_data_mining_on_student_behavior_and_cognitive_style_data_for_improving_e-learning_systems_A_case_study> |
| abstract | In this research we applied classification models for prediction of students’ performance, and cluster models for grouping students based on their cognitive styles in e-learning environment. Classification models described in this paper should help: teachers, students and business people, for early engaging with students who are likely to become excellent on a selected topic. Clustering students based on cognitive styles and their overall performance should enable better adaption of the learning materials with respect to their learning styles. The approach is tested using well-established data mining algorithms, and evaluated by several evaluation measures. Model building process included data preprocessing, parameter optimization and attribute selection steps, which enhanced the overall performance. Additionally we propose a Moodle module that allows automatic extraction of data needed for educational data mining analysis and deploys models developed in this study |
| data | Models were based on the following data:  number of quizzes passed or failed; number of messages  sent or read on the forum; total time spent on assignments,  quizzes, and forum; and final mark obtained by the student  in the course. |
| citOthers | Using data mining on student behavior and cognitive style data for improving e-learning systems: A case study. Available from: https://www.researchgate.net/publication/261581685\_Using\_data\_mining\_on\_student\_behavior\_and\_cognitive\_style\_data\_for\_improving\_e-learning\_systems\_A\_case\_study [accessed Apr 22 2020]. |
| futurework | In future work we plan to evaluate more classification and clustering algorithms in order to make even better fitting of models to web usage data. Additionally, enriching the student data with even more descriptors (e.g. data gathered through social network analysis) of their behavior on the educational system is definitely a worthy investment. Specifically, informal learning becomes more and more important because learning can happen anywhere at any time and analysis of informal learning data in distance learning systems provides a growing research area.58 This will open a true potential for analysis of student behavior, more than has ever been possible in the traditional learning context |
| dataA | 22-Apr-2020 |
| dataR | 22-Apr-2020 |
| area | LA |
| conclusion | Describing students with their cognitive styles seems natural in the educational context, and this research encourages further usage of this kind of data. So we built a clustering model that identifies the groups of students with similar cognitive styles and different success. Defined models are evaluated and used for construction of Moodle module that can help educators for two purposes: for distinction of students they can collaborate with or identification of students that need extra attention on that course, adaption of learning materials to better fit some specific cognitive styles or even recommend courses to students that better fit their cognitive style |
| year | 2012 |
| tags | ELearning, Student, Behaviour, DM |

### 

### T74-64 Title : Using learning analytics to identify successful learners in a blended learning course

|  |  |
| --- | --- |
| **subject** | **description** |
| serial | 64 |
| year | 2013 |
| area | LA |
| title | Using learning analytics to identify successful learners in a blended learning course |
| link1 | <https://www.researchgate.net/publication/259041885_Using_learning_analytics_to_identify_successful_learners_in_a_blended_learning_course> |
| abstract | In this paper, students' practices while using a Learning Content Management System in a blended learning environment were examined. This is a case study involving 337 students who attended an academic course based upon a blended learning approach over three years using Moodle. Eighteen variables depicting the students' perceptions of Moodle, as well as their interaction with it, were examined using four complementary data mining and statistical analysis approaches: visualisation, decision trees, class association rules and clustering. The analysis of the collected data shows that failure in the course was associated with negative attitudes and perceptions of the students towards Moodle. On the other hand excellent grades were associated with increased use of the LCMS. Requirements elicitation of a learning analytics dashboard, are also discussed. |
| authors | Sotiris Kotsiantis; Nikolaos Tselios; Andromahi Filippidi; Vassilis Komis |
| keywords | learning analytics; blended learning; learning content management systems; case study; interaction data; perceptions; higher education; Moodle. |
| points | Investigated ten different variables related to the students’ activities:  assignment\_view, course\_view, forum\_add\_post, forum\_view, glossary\_view, questionnaire\_view, resource\_view, user\_view, and final course grade. |
| rating | 8 |
| results | Four different methods were applied to explore the data illustrating students’ activity in the Moodle environment: (a) visualisation of each variable distribution using R version 3.0.1 (Graham, 2011); (b) C4.5 decision tree algorithm (Quinlan, 1993) to identify which variables predict students’ pass or fail (whether they passed the lesson or not); (c) class association rules (Bing et al., 1998) indicating which variables were associated with their grade and (d) clustering using k-means implementation of Weka version 3.7.8 (Hall et al., 2009). Methods (b) and (c) due to their comprehensibility are considered suitable for decision making and quick inspection. In the following, each of the aforementioned methods is presented and discussed extensive |
| futurework | it is argued that other approaches to study students’ activity such as eye tracking sessions (Katsanos et al., 2010) and task modelling techniques (Tselios and Avouris, 2003; Tselios et al., 2008a; Tselios et al., 2008b) could enrich the effectiveness and robustness of the presented approach. Similar Learning Analytics techniques should be also applied in other educational contexts as well as in different web-based collaborative learning platforms such as wikis (Tselios et al., 2011a; Tselios et al., 2011b) to investigate the generalisability of the proposed approach. |
| limitations | The participants were students from a Department of Social Sciences with specific characteristics such as age, gender, computer skills and experience etc. Moreover, the results obtained do not explain how the students have benefited from their engagement with the LCMS system. Other studies using similar approaches (Romero et al., 2008; Romero and Ventura, 2010; Romero et al., 2013a; Romero et al., 2013b), share the same limitations, thus stressing the need of conducting more studies in a variety of settings. |
| citOthers | https://www.researchgate.net/publication/259041885\_Using\_learning\_analytics\_to\_identify\_successful\_learners\_in\_a\_blended\_learning\_course [accessed Apr 22 2020]. |
| tags | Blended Learning, Performance, Learners, LA |

### T75-65 Title : xxxx

|  |  |
| --- | --- |
| subject | description |
| serial | 65 |

### T76-66 Title : Data Mining and Gamification Techniques in Adaptive E-Learning : Promises and Challenges

|  |  |
| --- | --- |
| **subject** | description |
| **serial** | 66 |
| **dateA** | 01-Jun-19 |
| **dataR** | 07-May-20 |
| **title** | Data Mining and Gamification Techniques in Adaptive E-Learning : Promises and Challenges |
| **DOI** | 10.5120/ijca2018916275 |
| **keywords** | adaptive e-learning; e-learning; educational data; gamification; knowledge discovery in databases; learning management system; mining |
| **rating** | 8 |
| **avl** | Y |
| **year** | 2018 |
| **authors** | Reem S. Al-Towirgi,, Lamya F. Daghestani, Lamiaa F. Ibrahim |
| **abstract** | Educational Data Mining EDM is an emerging discipline. It concerned with extracting useful information from large educational data. It serves education improving by presenting information to facilitate the process of decision making. EDM has many methods and applications the context of e-learning. Gamification is the process of using mechanics and dynamics of games onto non-game context to promote the desired behavior. An emerging type of learning method is the adaptive e-learning. This paper discusses the state of the art of EDM and gamification methods to build adaptive e-learning system |
| **conclusion** | EDM and gamification are novel domains. They apply the methods and techniques of data mining and gamification in adaptive educational context. The goal of using EDM is to facilitate the decision making about the learning process to increase its effectiveness.  This paper surveys the state of the art of applications of data mining in e-learning. There are many studies conducted using different methods of data mining. Many studies used EDM for several goals such as predicting student's performances, grouping students according to their data, classify contents of the course, producing a recommendation for students and visualize student information  Most of EDM studies results have to be interpreted effectively to help instructors in decision making. Decisions that can be made to increase the effectiveness of e-learning are such as adapting the course contents based on the student's categories, improving the course design according to students usage, giving feedback to the student to lead them to change their behavior, detecting students at-risk early depending on their assignment or quizzes marks |
| **futurework** | Because of the fact that EDM is fast growing and its application was useful, It is expected that many applications will be proposed and implemented in the coming few years to help the learning process |
| **link1** | <https://www.ijcaonline.org/archives/volume180/number13/28926-2018916275> |
| **publication** | International Journal of Computer Applications |

### 

**T77-67 Title : Using process mining to analyze students' quiz-taking behavior patterns in a learning management system**

|  |  |
| --- | --- |
| subject | description |
| serial | 147 |
| title | T156-146 Title : Using process mining to analyze students' quiz-taking behavior patterns in a learning management system |
| link1 | <https://www.jstage.jst.go.jp/article/ipsjjip/24/4/24_740/_pdf> |
| dataR | 08-May-20 |
| area | EDM |
| abstract | The use of data mining in the education sector has increased in the recent past. One reason for this is the wide use of learning management systems (LMS), which store data related to learning activities. The goal of this research is to predict individual learning styles using the Moodle LMS by analyzing log data using a data mining technique. We use the Waikato environment for knowledge analysis (Weka), as the data mining tool and compare the differences in the performance of several data mining techniques using course log data. Our experimental results show that the J48 decision tree classification algorithm works best with our dataset. We also propose a group learning map that visualizes the learning styles in a class, which can help instructors and learners achieve learning outcomes more effectively. |
| DOI | 10.2197/ipsjjip.24.740 |
| RO | Predict individual learning styles using the Moodle LMS by analyzing log data using a data mining technique |
| results | J48 decision tree classification algorithm works best with our dataset. We also propose a group learning map that visualizes the learning styles in a class, which can help instructors and learners achieve learning outcomes more effectively. |

### T78-68 Title : xxxx

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| --- | --- |
| subject | description |
| serial | 68 |
| area | LA |
| title | blank |

### T79-69 Title : xxxx

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| --- | --- |
| subject | description |
| serial | 69 |
| area | LA |
| title | blank |

### T80-70 Title : xxxx

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| --- | --- |
| subject | description |
| serial | 70 |
| area | LA |
| title | blank |

### T81-71 Title : xxxx

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| --- | --- |
| subject | description |
| serial | 71 |
| area | LA |
| title | blank |

### T82-72 Title : xxxx

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| --- | --- |
| subject | description |
| serial | 72 |
| area | LA |
| title | blank |

### T83-73 Title : xxxx

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| --- | --- |
| subject | description |
| serial | 73 |
| area | LA |
| title | blank |

### T84-74 Title : xxxx

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| --- | --- |
| subject | description |
| serial | 74 |
| area | LA |
| title | blank |

### T85-75 Title : xxxx

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| --- | --- |
| subject | description |
| serial | 75 |
| area | LA |
| title | blank |

### T86-76 Title : xxxx

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| --- | --- |
| subject | description |
| serial | 76 |
| area | LA |
| title | blank |

### T87-77 Title : xxxx

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| --- | --- |
| subject | description |
| serial | 77 |
| area | LA |
| title | blank |

### T88-78 Title : xxxx

|  |  |
| --- | --- |
| subject | description |
| serial | 78 |
| area | LA |
| title | blank |

### T89-79 Title : xxxx

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| --- | --- |
| subject | description |
| serial | 79 |
| area | LA |
| title | blank |

### T90-80 Title : xxxx

|  |  |
| --- | --- |
| subject | description |
| serial | 67 |
| area | LA |
| title | blank |

**T11-T100 : LA (1-90)**

**T101-T150 : GBL(91-140)**

**T151-T200 : PM (141-190)**

## Gamification (Game) / Game Based Learning (GBL)

### T101-91 Title : Improving Student Performance through Gamification - A user study

|  |  |
| --- | --- |
| **subject** | **description** |
| serial | 91 |
| year | 2018 |
| area | Game |
| title | Improving Student Performance through Gamification - A user study |

### T102-92 Title : The effects of gamification elements in e-learning platforms

|  |  |
| --- | --- |
| **subject** | **description** |
| serial | 92 |
| year | 2018 |
| area | GBL |
| title | The effects of gamification elements in e-learning platforms |

### T103-93 Title : Gamification in e-learning : A Moodle implementation & its effect on student engagement & performance

|  |  |
| --- | --- |
| **subject** | **description** |
| serial | 93 |
| year |  |
| area | GBL |
| title | Gamification in e-learning : A Moodle implementation & its effect on student engagement & performance |

**T11-T100 : LA (1-90)**

**T101-T150 : GBL(91-140)**

**T151-T200 : PM (141-190)**

[Top](#_2e8teajfv8gz)

## Process Mining(PM)

### T151-141 Title : Prediction of Student Success Through Analysis of Moodle Logs : Case Study

|  |  |
| --- | --- |
| **subject** | **description** |
| serial | 40 |
| year | 2019 |
| area | PM |
| title | Prediction of Student Success Through Analysis of Moodle Logs : Case Study |
| link1 | <https://bib.irb.hr/datoteka/939844.ce_31_48061.pdf> |

### T152-142 Title : Web usage Mining for Predicting Final Marks of Students that use Moodle Courses

|  |  |
| --- | --- |
| **subject** | **description** |
| serial | 142 |
| year | 2010 |
| methods | Classification, Decision Tree |
| link1 | <https://www.researchgate.net/publication/229891919_Web_usage_mining_for_predicting_marks_of_students_that_use_Moodle_courses> |
| area | PM |
| title | Web usage Mining for Predicting Final Marks of Students that use Moodle Courses |

### T153-143 Title : Performance Analysis and Prediction in Educational Data Mining: A Research Travelogue

|  |  |
| --- | --- |
| **subject** | **description** |
| serial | 143 |
| year | 2015 |
| factors | As per Paper |
| RO | comprehensive survey, a travelogue (2002-2014) towards educational data mining and its scope in future |
| methods | Different |
| data | Different |
| link1 | <https://research.ijcaonline.org/volume110/number15/pxc3901007.pdf> |
| futurework | Other than academic attributes, there are large numbers of factors that play significant role in prediction, which includes oncognitive factors (set of behaviors, skills, attitudes). Integrated Models/Frameworks are required for all the stakeholders of an Institution; hence ensuring sustainable growth for all (Management, Teachers, Students and Parents). |
| title | Performance Analysis and Prediction in Educational  Data Mining: A Research Travelogue |
| area | PM |
| RQ | Survey of papers published in Educational Data Mining. Predicting Academic Performance with Pre/Post Enrollment Factors.; Comparison of Data Mining Techniques in predicting academic performance; Correlation among Pre/Post Enrollment Factors and Employability. Other areas of Education |
| results | There is a clear need for unified approach |
| authors |  |

### T154-144 Title : Indicators of Good Student Performance in Moodle Activity Data

|  |  |
| --- | --- |
| **subject** | **description** |
| serial | 144 |
| year | 2016 |
| RO | analysis of Moodle activity data focusedon identifying early predictors of good student performance |
| RQ | Early submission is a good sign, a high level of activity is predictive of good results and evening activity is even bet-ter than daytime activity. |
| factors | Grades, Assignment Submissions, Logs |
| link1 | <https://www.researchgate.net/publication/290527303_Indicators_of_Good_Student_Performance_in_Moodle_Activity_Data> |
| futurework | Identifying Outliers |
| title | Indicators of Good Student Performance in Moodle Activity Data |
| data | Logs, Moodle Data |
| area | PM |
| methods | Table, Statistics, Visualisaiton |
| results |  |
| authors |  |

### T155-145 Title : Analysis of Student Behavior and Success Based on Logs in Moodle

|  |  |
| --- | --- |
| **subject** | **description** |
| serial | 145 |
| year | 2018 |
| title | Analysis of Student Behavior and Success Based on Logs in Moodle |
| factors | Final Grades, Events |
| link1 | <https://bib.irb.hr/datoteka/939844.ce_31_48061.pdf> |
| data | Logs, Grades |
| area | PM |
| RQ | RQ1: To what extent are individual variables derived from log data a reliable predictor of academic success?  RQ2: What is the level of similarity in student LMS usage between genders? |
| RO | Relationship of Activity on Grades |
| methods | Visualisation; Statistics |
| authors | Nikola Kadoić and Dijana Oreški |
| abstract | Today, it is almost impossible to implement teaching processes without using information and communication technologies (ICT), especially in higher education. Education institutions often use learning management systems (LMS), such as Moodle, Edmodo, Canvas, Schoology, Blackboard Learn, and others. When  accessing these systems with their personal account, each student’s activity is recorded in a log file. Besides analyzing the raw data from log files directly, there is an option to use Moodle plugins that provide learning analytics and enable  the faster analysis of students’ behavior on LMS. In this paper, some of these plugins are presented. However, this paper is focused on analyzing the log files of a course  implemented on the LMS Moodle at the Faculty of Organization and Informatics at the University of Zagreb. The results of the students’ behavior, based on logs in  Moodle, will be interpreted in terms of student success. |
| points | A log is a list of a students’ events in which each line contains a timestamp as well as one or more fields that hold information about the activity performed [23]. A Moodle log consists of the time and date it was accessed, the Internet Protocol  (IP) address from which it was accessed, the name of the student, each action completed (i.e., view, add, update, or delete), the activities performed in different modules (e.g., the forum, resources, or assignment sections), and additional information about the action [23]. The stored data can be useful for data mining algorithms  According to experience of teachers of the course currently being studied, students often complete their assignments (e.g., write essays, answer questions, or study  for exams) in the last moments before a deadline. The idea of next analysis is to determine the distribution of students’ logs on the system on the days before the two exams. |
| method | Moodle course log was collected after the spring semester of a blended course  called "Business Decision Making". A total of 73 students registered with Moodle, and 180-minute teaching lectures and seminars were held every Wednesday. |
| conclusion | Results are potentially beneficial in the early detection of students experiencing difficulties in a course. Both teachers and students benefit from this kind of  research, as teachers can identify excellent students for collaboration and students find out how to give greater effort to obtain good results. In the conducted research, the female students are more active and successful in the course than are the male  students. There is a correlation between the number of logs in the e-course and the final grades. The students were most active in the test weeks and, specifically, on the day before the tests. Students can be characterized as “lastminute” students, as they perform their obligations as late as possible in terms of the deadline and are active in the late hours. However, this cannot be generalized because the research was conducted in only one course. Also, the research covered only informatics students. |
| futurework | Future research, the analysis will be performed across several courses. Additionally, students from other disciplines, not only informatics, will be included in future research. |
| results | Surprisingly, for the students with the highest grade, most of the course activity was done on the day before lectures, seminars, and tests hours of the day during which students were logged into the course, and the opening was concentrated from 11:00 on. During the afternoon, a number of logs persist, but this decreases in the evening. In the period after the midnight, there is no activity on the e-course.Page views occurred mostly between 17:00 and 20:00 on the day before the first test day (04-18-2017) and between 15:00 and 16:00 on the day before the second test day (06-13-2017). In both cases, there is a significant number of logs in the late hours of the day. During these times, most students downloaded test materials and started to study. However, course activity during the late hours is more conspicuous for the first test than it is for the second.  Weekly analysis showed that the highest number of logs appear on the day before test days.  Female students have a higher number of logs than their male colleagues. Differences between genders is also visible in the average grade received. Female students have a higher average grade than male students.  The **highest number of logs is achieved by the students with the highest grades**,  4 and 5. To investigate if there is any correlation between specific activities on the LMS and student grades, we have performed correlation analysis  The results indicate a statistically significant correlation among students’ grades and the opening of files. The correlation is positive, which indicates that students with a higher frequency of file openings have higher grades. There is a lack of association between grades and other logs in the course. students who are active in forum discussions opened files more often. |
| dateR | 22-Apr-2020 |
| dateA | 01-Feb-2020 |
| rating | 8 |
| reading | Jovanovic, Vukicevic, Milovanovic, and Minovic [33] defined a classification model |

### T156-146 Title : Using process mining to analyze students' quiz-taking behavior patterns in a learning management system

|  |  |
| --- | --- |
| **subject** | description |
| **serial** | 146 |
| **area** | PM |
| **title** | Using process mining to analyze students' quiz-taking behavior patterns in a learning management system |
| **link1** | <https://www.sciencedirect.com/science/article/pii/S0747563217306957> |
| **points** | Process-centric approach to analyze student behavior in Moodle were employed. Students' behavior and interaction patterns in quiz-based activities were studied. Standard and non-standard behavior were identified using process mining. Four different behavior patterns were identified. |
| **abstract** | The aim of this paper is to explore students' behavior and interaction patterns in different types of online quiz-based activities within learning management systems (LMS). Analyzing students' behavior in online learning activities and detecting specific patterns of interaction in LMS is a topic of great interest for the educational data mining (EDM) and learning analytics (LA) research communities. Previous studies have focused primarily on frequency analysis without addressing the temporal aspects of students' learning behavior. Therefore, we apply a process-oriented approach, investigating perspectives on using process mining methods in the context of online learning and assessment. To explore a broad range of possible student behavior patterns, we analyze students' interactions in several online quizzes from different courses and with different settings. Using process mining methods, we identify specific types of interaction sequences that shed new light on students’ quiz-taking strategies in LMS. We believe that these findings bring important implications for researchers studying student behavior in online environments as well as practitioners using online quizzes for learning and assessment. |
| **conclusion** | use of complementary methods of Data mining and Process mining in e-Learning systems can improve the quality of teaching, increase its availability and effectiveness |
| **dateA** | 22-Apr-2020 |
| **dataR** | 22-Apr-2020 |
| **myres** | I will use this paper for my work |

### T157-147 Title : Mining Activity Log Data to Predict Student's Outcome in a Course

|  |  |
| --- | --- |
| subject | description |
| serial | 147 |
| title | Mining Activity Log Data to Predict Student's Outcome in a Course |
| dateR | 09-May-20 |
| abstract | Use of a learning management system (LMS) is very common, which provides support to teaching staff for communication, delivery of resources and in design of learning activities. The widespread use of technologies like LMS, provide large amounts of data. Research shows that higher education institutes can make use of this data to extract data-driven insights to understand the learning process and benefit the students by supporting them in their academics. In this study we used several machine learning algorithms to predict a student's outcome in a course using LMS trace data and assessment scores. Selection of the courses is based on the extent the LMS is used and is divided into two categories; distance and internal. This study confirms the importance of LMS data and assessment scores in the prediction of academic performance. However, frequent use of LMS may increase the trace data but it is not necessary to improve the predictive accuracy. Predictive models developed for courses, without considering the context of use of LMS data, may not generalize the effects of LMS trace data on student's outcome in the course. |
| area | Learning analytics; prediction; Classification; Education data mining; |
| link1 | <https://dl.acm.org/doi/pdf/10.1145/3322134.3322140> |
| DOI | https://doi.org/10.1145/3322134.3322140 |
| tools | For conducting experiments, we used python module scikit-learn [29]. Scikit-learn is an increasingly popular machine learning library that integrates a wide range of algorithms for supervised, unsupervised and semi-supervised problems. This provides a user-friendly environment for non-experts in machine learning and reusable in different scientific platforms. |
| case | The courses were taught for a duration of sixteen weeks. Number of assessments in  Each course varied from 2 to maximum 5 assessments. Two variables; Log V1 and log V2 represent the online activity level in the courses. Log V1 represents the total unique activities performed in the course, whereas log V2 shows the total number of records in the log of the course. The activities present in Moodle are mostly record the interaction between student and instructor |
| conclusion | selected different types of courses in terms of their instruction format (distance vs internal) and compared several machine learning methods that includes, random forest,  logistic regression, naïve Bayes, LDA and ensemble method to predict the outcome of students in the course using LMS trace data and assessment scores. |
| method | Total number of experiments is 64. There are two kinds of attributes in each  dataset, one is the count of total online activities and second is assessment scores (if available at that time of the week). The aim was to predict the outcome after every week into two classes; ‘at-risk’ and ‘not-at-risk’ of failing the course |
| results | results confirm that LMS data have got discriminating power but not more than assessment scores. Courses in which students used LMS more frequently and number of assignments are more than 3, the accuracy of predictive models for such courses were high. Our findings show that a combination **of LMS data and assessment scores can improve the accuracy of predictive models**. In addition to this it is also confirmed that  more LMS data doesn’t directly improve the accuracy, which means just count of activities is not enough; it needs to be investigated further that what kind of activities differentiate  between groups of students |
| gap | study confirms the importance of LMS data with a combination of assessment scores in prediction of student’s academic performance. However, it is not enough to generalize  the conclusion as the data used in the study is limited to one institution and there are more data that can be used for classification. |
| data | The data extracted from two different sources: one from official LMS (called as Stream) which produces detailed activity logs for each student and resulted in a total of 6,83672  raw records and the second source is university official students. management system (SMS) which stores students’ profile information, their assessment score and information that are required during the registration process and which results in a total of 400 records(number of students). The trace data extracted from LMS; when students are interacting with the Moodle. Following are some examples of Moodle features/components that were accessed during the course; assignments, resources, forum, book, quizzes, chat and course. The trace data are numerical which represents the number of times student used particular component of Moodle |
| comments | Data preprocessing involves steps to generate a dataset that is in a format on which algorithms can be applied. This step is not straight forward, because there are various sources of data. The main challenge is to identify the relevant data, capture it, extract  it and integrate data to get useful information. One of the challenges faced during the extraction process was that both sources have different primary key for course related  information, so we need to write a script to extract information and integrate from both sources. The final dataset includes academic scores and activity data that can be captured from log, which is mostly referred to and LMS engagement data. Data extracted from both sources were encrypted, in order to take care of student’s privacy. Other preprocessing steps involve handling missing values, looking for outliers and changing some data format of data to make it relevant for the database |
| myres | Assessment + Profile + Logs -> Predict (using Machine Learning) |
| notes | Pictures added in different doc |
| type | paper |
| publication | ICBDE'19: Proceedings of the 2019 International Conference on Big Data and Education March 2019 |
| year | 2019 |

# Articles/Thesis

### Txx-xx-1 Title : Learning Analytics – Predicting Academic Performance

|  |  |
| --- | --- |
| serial | description |
| serial |  |
| link | <https://degreesofbelief.roryquinn.com/learning-analytics-predicting-academic-performance> |
| title | LEARNING ANALYTICS – PREDICTING ACADEMIC PERFORMANCE |
| type | Article |
| method | Study tracked the progress of more than 34,000 students enrolled in third level education in Ireland in 2007/2008, found that 76% graduated over the following ten years. Completion rates varied somewhat by type of college, subject and gender. Overall 58% of students graduated on time. Although apparently these figures compare well internationally, one can see that more than 40% of third level students in this cohort didn’t graduate on time and nearly a quarter hadn’t graduated in the following ten year period |
| highlights |  |
| dateR | 05-May-20 |
| conclusion | Building a model that can predict academic performance is one thing, operationalising it is another. There are a number of factors to be considered in that case.   * In our study, because of small sample size, failing students and early exiting students were combined into a single category. Ideally these may need to be differentiated since a different approach may be required for each. * Once a student has been identified as at risk of failure what form will intervention take? Identifying students at-risk of drop out or failure is not much use if an intervention doesn’t succeed in preventing those outcomes for at least some of them. * Cost-Benefit Analysis. Collecting data and training a model to predict student performance is a relatively low-cost endeavour. Even if only a few extra students in any particular cohort graduate, the benefits may outweigh the costs. * Before such a model could actually be deployed in a ‘live’ environment, model interpretability would need to be considered in the context of GDPR. |

### Txx-xx-1 Title : Prediction of student performance using data mining techniques in higher education domain

### 

|  |  |
| --- | --- |
| subject | description |
| serial |  |
| title | Prediction of student performance using data mining techniques in higher education domain |
| type | Thesis |
| year | 2013 |
| link1 | <https://shodhganga.inflibnet.ac.in/handle/10603/6443> |

### Txx-xx-1 Title : Possibilities for Improving Student Success Using Predictive Analytics

### 

|  |  |
| --- | --- |
| subject | description |
| serial |  |
| title | Possibilities for Improving Student Success Using Predictive Analytics |
| type | Thesis |
| year | 2014 |
| link1 | <http://rpgroup.org/system/files/Predictive%20Analytics%20Environmental%20Scan_FINAL.pdf> |

### Txx-xx-1 Title : Prediction of Student Performance using Data Mining Techniques in Higher Education Domain

|  |  |
| --- | --- |
| subject | description |
| serial |  |
| title | Prediction of Student Performance using Data Mining Techniques in Higher  Education Domain |
| type | Thesis |
| year | 2014 |
| link1 | <http://shodhganga.inflibnet.ac.in/handle/10603/30316> |

### Txx-xx-1 Title : Predictive Analytics For Student Success : Developing Data-Driven Predictive Models of Student Success : Final Report

|  |  |
| --- | --- |
| subject | description |
| serial |  |
| title | Predictive Analytics For Student Success : Developing Data-Driven Predictive  Models of Student Success : Final Report |
| type | Thesis |
| year | 2015 |
| link1 | <http://docplayer.net/983832-Predictive-analytics-for-student-success-developing-data-driven-predictive-models-of-student-success.html> |

### Txx-xx-1 Title : Developing Data-Driven Predictive Models of Student Success

|  |  |
| --- | --- |
| subject | description |
| serial |  |
| title | Developing Data-Driven Predictive Models of Student Success |
| type | Thesis |
| year | 2015 |
| link1 | <http://www.umuc.edu/documents/upload/developing-data-driven-predictive-models-of-student-success-phase-two.pdf> |

### Txx-xx-1 Title : Data Mining Application for Educational System

|  |  |
| --- | --- |
| subject | description |
| serial |  |
| title | Data Mining Application for Educational System |
| type | Thesis |
| year | 2015 |
| link1 | <http://shodhganga.inflibnet.ac.in/handle/10603/38865> |

### Txx-xx-1 Title : Helping further and higher education organisations to analyse and understand their data

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| subject | description |
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| title | Helping further and higher education organisations to analyse and understand their data |
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### Txx-xx-1 Title : Educational Data Mining/Learning Analytics issue brief overview

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| subject | description |
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| title | Educational Data Mining/Learning Analytics issue brief overview |
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Title

**SubTitle**

# Heading 1

## Heading 2

### Heading 3

#### Heading 4

|  |  |  |
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| pID | Technique | Description |
| [66](#_fy1dcchyelxc) | Classification | A classifier is a mapping from a feature space X to a discrete set of labels Y [28]. Classification provides a collection of labeled patterns and tends to predict class label for new unlabeled patterns.  Chen et al. [29] used decision tree based on student behavior to discover students group with same characteristics and same reaction to a specific strategy. The decision tree will help the instructor to analyze student historical data weblog and to estimate the effectiveness of a certain strategy to achieve the desired pedagogical goals.  Minaei-Bidgoli and Punch [30] proposed an approach to classifying students based on extracted data from educational system log to predict their final grade. They used a combination of four classifiers to increase the accuracy of the classification. Results show that the total number of correct answers is the most important features of the classification  Kotsiantis et al. [31] used Naïve Bayes to detect learner's performance based on demographic information and written assignments. This will help the instructor to construct the software support tool for enhancing students' performance.  Cocea and Weibelzahl [32] investigate if the log data can estimate the motivational level of the student. Using the decision tree, the researchers find that the reading time was an important factor to detect the motivation.  Hamalainen and Vinni [33] used classification to detect student success in the middle of the course. They used Naïve Bayes based on exercise points to detect the performance as early as possible.  Romero et al. [24] used C4.5 algorithm to classify students into different groups according to final mark based on their activities in the LMS. The results can be used to make decisions to improve course activities or to detect learners with learning problems.  In a summary, the review found that all classification studies are oriented toward the student's behavior. For example, studies [30],[31] and [33] classified students according to their learning performance whereas [24],[29] and [32] classified students based on their characteristics.  Regarding the algorithm used, most of the classification studies used decision tree [29], [30], [32], [24] and Naïve Bayes [31][33]. A decision tree is the easiest method in interpreting and explaining results and it needs a little effort for data preparation. Naïve Bayes is simple, fast and easy to implement. |
| 66 | Prediction | Prediction is the process of developing a model to infer what behavior will predict the student success or failure in the learning outcome [18]. Statistical methods are used in prediction studies such as multiple regression and logistic regression. LMS variables can be used to predict the performance of student such as the number of assignment completed, the number of quizzes passed, and the number of posts in discussion forum etc.  In [19], Macfadyen and Dawson analyzed LMS student usage of online course. They use correlation analysis, multiple regression analysis, and logistic regression to predict the final grade. They found that final grade was predicted depending on the total number of posted topics in the forum, total number of sent mail and the total number of completed assignment  Abdous et al. in [20], study the relationship between the question type asked by a student in the forum and his final grade. In their paper, researchers classify the questions into four themes: class check-in, deadline/schedule, evaluation/ technical and learning/comprehension. Results showed that students that asked about learning/comprehension had a higher final grade.  Thakur et al. in [21] used logistic regression and neural network model to predict student success. The number of completed assignments was the basic predictor of student success and failure, followed by the completed quizzes and submitted posts.  In [22] Jo et al. used multiple regression analysis and found that the regularity of learning intervals was an important predictor of final grade while total time and login frequency were not important predictors  Lee et al. [23] used multinomial logistic regression to predict the final grade based on used features. Results showed that assignments are the strongest predictor of the final grade in face-to-face courses, and quizzes are the strongest predictor of the final grade in online courses.  This review found that all prediction studies are similar in predicting the final grade but differ in the type of predictor variable. For example, studies [19], [21] and [23] found that the **assignment is the strongest predictor of the final grade whereas the strongest predictor in [20] and [22] are the type of question asked in the forum and regularity of learning intervals respectively**. Regarding the methodology used, most of the prediction studies used logistic regression [19], [20], [21], [23] and multiple regression [19], [21] because of ordinal nature of predicted variable (the final grade) |
| 66 | Association Rule Mining | Association rule mining discovers the relationship between variables in databases. It identifies rules that discovered in databases based on some measures of interesting [34].  Zaiane [35] used association rule mining to build an agent that can recommend activities on the learning system. Based on the history of learner navigation, the material of the course will be improved. Recommendations will help the learner to navigate the materials by facilitate finding relevant resources and assist the learner to choose activities that improve their performance.  Lu [36] propose a framework of a recommender system to help students to find the wanted learning materials. Using association rule mining, this recommender system can help the students to learn more effectively by providing personalized learning materials.  Ramli [37] used association rule mining to optimize the course content. By applying Apriori algorithm to log data, they mine the relationship between visited pages. This will be helpful for an instructor to increase the performance of web services through improving the website in terms of its contents, structure, presentation, and delivery.  Markellos et al. [38] analyzed the weblog data using association rules to produce recommendations to users in the learning system. They used Apriori algorithm on learning materials to determine the most suitable one for the student.  Romero et al. [24] used the Apriori algorithm for association rule mining. Based on student's data from weblog, authors found some interesting rules that may help the instructor to pay attention to students that prone to failure and help them to success  All studies used association rule mining are used for optimizing the e-learning contents according to the students interesting. Contents such as activities [35], learning materials [36][38], web pages [37], messages [24] will recommend to the student for providing a personalized learning environment |
| 66 | Clustering | Clustering is a technique used to group a dataset into smaller subsets of similar objects or clusters [24]. Clustering can be used to group learners depending on their behavior or learning difficulties. Different objects can be clustered in e-learning, such as students, courses, and content. Romero et al. [24] grouped students based on their activities in the LMS. These activities include the number of assignments and quizzes and participation in discussions. Clustering was performed using the k-means algorithm to group students into three clusters: very active students, active students, and non-active students. Their results can be helpful for student grouping in collaborative activities.  Abdous, He and Yen in [20], categorized question themes using a hierarchical cluster analysis into four categories: class check-in, deadline/ schedule, evaluation/technical and learning/comprehension.  Valsamidis et al. [25] categorized courses based on usage rate using the k-means algorithm. They found two clusters: high activity courses and low activity courses. Researchers proposed a way for measuring the quality of the course depending on the number of viewed pages by students for each session. Also, they investigated the relationship between the the quality of the course and total course score.  Lust et al. [26] used k-means to group students based on their use of LMS and self-reported self-regulation strategies. They found four clusters reflecting tool used and strategy. Clusters are self-regulated and deeply oriented students, disorganized students, undefined students and inconsistent students.  In [27], Yildiz et al. cluster students depending on usage data (such as quiz score, exam score) using three clustering methods to find the best approach for estimating the final grade: k-means, fuzzy c-means, and subtractive clustering. They found that fuzzy c-mean is the best method for predicting student performance.  Lee et al. [23] applied expectation maximization and k-means to cluster courses depending on instructor and students usage data. Clusters differ in terms of assignments, quizzes, discussion topics and wiki pages. They found three students clusters and three instructor clusters based on LMS features used.  The results of clustering studies showed that the most commonly used algorithm was the k-means algorithm because it is one of the most popular and simplest algorithms used in data mining. Regarding the clustering object, students is the most used clustering object [24][25][26][27]. Another clustering objects were courses [25] and course contents [20]. |
| 66 | Visualisation | Distillation of data for human judgment uses techniques for data representation to enable humans to understand it quickly and easily [18]. The most popular and effective technique is a visualization. Information visualization [39] is a computer graphics and user interface branch concerned with the representation of an interactive image to the user. This will facilitate the analysis of vast amount of information through charts, scatter plots or 3d representation.  Shen et al. [40] present a Data Analysis Center system to present student's data such as solved assignment and quizzes marks. This system can show the place of the learner in the class and define the weakness of the learning process. It can help teachers to analyze learner's patterns and to construct the materials efficiently.  Romero et al. [24] used GISMO tool to visualize data from Moodle log such as graphs representing. Course access, resources access, discussion participating. This will allow the instructor to be aware of what is happening in the learning process.  Valsamidis et al. [25] used a Markov clustering algorithm which combines cluster analysis and graphical representation to represent the relationship between students. The similar students were grouped visually to help interpreting results  Arnoled and Pistilli [41] developed a Course Signals application that used a dashboard to provide a real-time display of student performance to instructors and students. They get a positive result on student's grades when using this application. Thakur et al. in [21] examine LMS usage data to investigate the constancy in student's marks over the course by using heat maps. The result of the investigation was that the senior student's grades were stable whereas the freshmen grades tended to be unstable.  Lee et al [23] used clustergram of the features used by students in LMS to help visualization of student’s behavior among the course and relate it to the final grade  As a result, all studies of visualization are focused on students' performance in the learning process to get the better understanding of student's behavior and detect student which are at-risk |

## T07 LA : Definitions

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| pID | **subject** | description |
| 66 | **EDM** | A special field of data mining that used in education context is called Educational Data Mining (EDM)  Educational Data Mining (EDM) extends from Data Mining (DM) field which attempted to achieve many requirements that could not be achieved by traditional methods using statistics, artificial intelligence, pattern recognition and machine learning [11]. EDM results can be used to support learning and teaching in an innovative way through learning analytics [18]  The purpose of EDM is to extract useful information from large learning dataset collected from online learning platforms to improve learning [18]. It provides useful information to students, faculty, and administrators such as: predicting student success or failure, extracting valuable pattern and creating a model for student learning, and evaluating e- learning process, Examining the relationship between students characteristics and learning outcome, monitoring student persistence and informing instructional design [12] |
| 66 | **EDM Methods** | Several methods and techniques are used in EDM researches. Baker and Yacef [10] suggest that EDM is used to improve student model, improve domain model and analyze the support of learning system. They categorized the EDM methods into prediction, clustering, association rule mining, a discovery with models and distillation of data for human judgment  Romero and Ventura [11] found that the most DM methods used are regression, clustering, classification and association rule mining. They categorized the applications of EDM into a visualization of data, providing feedback to support teachers, a recommendation  to students, predicting learner performance, modeling of students.  EDM can be used to analyze data from any interactive learning environment. In this paper, the focus will be on EDM researches that applied to higher education. These researches are presented in the following sections and categorized according to the method used |
| 66 | **LA** |  |
| 66 | **AA** |  |
| 66 | **Gamification** | Gamification is the process of using mechanics and dynamics of games onto non-game context to promote the desired behavior [6].  Gamification is different from serious games that create full- fledged games to achieve the same goal. Rather than creating an actual game, gamification grafts elements that make video games fun and effective and applying them to applications.  The concept of gamification is defined as "the incorporation of game design aspects in the implementation of software systems unrelated to games" [44]. Offering rewards, instant feedback, competition and freedom to fail to learners bring an additional layer of user engagement in the learning process.  Nowadays research is done to find out the probable relations between gamification-elements and learners’ motivation [45], [46]. |
| 66 | **DM** |  |
| 66 | **E-Learning** |  |
| 66 | **KDD** | Data mining or knowledge discovery in databases (KDD) is the process of extraction of interesting patterns from large dataset [4]. |
| 66 | **LMS** | To facilitate the interaction between students and teachers in e-learning, Learning Management Systems (LMSs) was created. Examples of popular LMS are Blackboard, Moodle, Edmodo, and Canvas [8]  **LMS features are categorized into four basic categories depending on what they support [9]: administration, content, assessment, and engagement**. Administration features concerned with course administration aspects such as calendar and announcements. Content features support accessing the course modules and linking to external resources. Assessment features facilitate the evaluation process through quizzes and assignments. Engagement features concerned with users participation such as discussion forums and collaboration activities. These features can be cooperated to enhance many different courses in different disciplines.  process through quizzes and assignments. Engagement features concerned with users participation such as discussion forums and collaboration activities. These features can be cooperated to enhance many different courses in different disciplines.  **Three important data attributes need to be considered while capturing educational data which are: time, sequence and context**. Time parameter concerned with the time of learning and the length of sessions. Sequence concerned with the order of building content and practice. Context helps in explain results and decide the availability of a model working,  Most of the LMSs store the users' data when they interact with the system in a large data set for further analysis [13]. These data are different from the traditional educational dataset in terms of being tall (number of students), wide (attributes for each student), long (in duration)  LMSs differs in terms of stored information and how they storing this information. Some LMSs store the number of times each property is used for every user while others store the updates of features used by each student over the days. Also, some LMSs use a relational database to store data while others use flat log files [14]  Information about learner's navigation through the course and how instructors support the students learning through course design create massive datasets. Researchers tend to analyze these data sets using the computational and statistical methods emerging from the big data field to discover a new pattern of learning and teaching [15][16]. This leads to a new field which uses the applications of data mining methods to an educational dataset called educational data mining (EDM) [17].  Educational Data Mining (EDM) extends from Data Mining (DM) field which attempted to achieve many requirements that could not be achieved by traditional methods using statistics, artificial intelligence, pattern recognition and machine learning [11]. EDM results can be used to support learning and teaching in an innovative way through learning analytics [18]  The purpose of EDM is to extract useful information from large learning dataset collected from online learning platforms to improve learning [18]. It provides useful information to students, faculty, and administrators such as: predicting student success or failure, extracting valuable pattern and creating a model for student learning, and evaluating e- learning process, Examining the relationship between students characteristics and learning outcome, monitoring student persistence and informing instructional design [1 |
| 66 | **Adaptive Learning** | The ability to identifying students who are at risk of failing a course is important for teachers to take corrective actions [42]. An emerging type of learning is the adaptive e-learning. Each student has their preferences, current skill and learning styles [43]. Adaptive E-learning is designed to offer personalized experiences to students according to his personality. Gathering data, analyzing and interpreting skill level and preferences of the user and applying the necessary adjustments to the system in order to fit the current ability of the learner is the main feature of this approach  Literature review modeled the adaptive learning environment from several perspectives [44]:  a) Domain model: during a learning process, this model focus on relationships between course material to adapt the content delivery and timing of courses.  b) Learner model: in this model, the system continues dynamically adjusted with respond to the user, his interaction with the system, his responses, and his personal characteristics.  c) Group model: this model analyzes groups of learners in individually find learning patterns in this groups.  d) Adaptive model: This model joins the adaptive theory of an adaptive learning environments ALE, at various levels of abstraction.  Adaptive e-learning is an emerging type of learning. Powerful adaptive e-learning system needs to be well designed. Some guidelines were proposed for designing an effective adaptive e-learning system:  First, using educational data mining EDM in adaptive e- learning systems will enhance the performance of E-learning system.  Second, finding out the probable relations between gamification elements and learners’ motivation in Adaptive E- learning system is very important to improve the Learning system. |
| 66 | **Game Mechanics** | Games mechanics are the elements that move the actions forward such as points, bonuses, and levels. Game |
| 66 | **Game Dynamics** | Game dynamics are the tools that help to figure out how to move the action forward such as achievements, competition, status, and altruism |
| 66 | **Serious Games** |  |
| 66 | **E-Learning** | E-learning is defined as training delivered in on a digital device to support individuals learning and achieve goals [1] |
| 2 | **LA** | HE institutions have used learning analytics data to identify and appropriately support students, whether they are at risk, underprepared or high performing (Prinsloo, Slade & Galpin, 2012). Recent technological advances have seen the advancement of learning analytics, such  as predictive analytics (Waller & Fawcett, 2013) and the development of apps to monitor student behaviour and provide data regarding well-being, mood and academic performance (Wang et al., 2014). |
| 2 | **LMS** | LMS, such as Blackboard and Moodle, attempt to replicate traditional classroom and institutional processes with the inclusion of formal assessments, courses and classes (Rahman and Dron, 2012). The Substitution Augmentation Modification Redefinition model, developed by Puentedura (2011), describes levels of technology integration and how it might impact learning and teaching. The model shows how technologies, such as LMS, may **transform and enhance previous educational methods if the technologies are appropriated, implemented and designed**. One of the **benefits of an LMS** is that it can provide built in learning analytics that can be used to monitor student behaviour and provide feedback to educators. **Data about students can be gathered objectively and with relative ease**. Research has suggested that learning analytics from an LMS may **help reduce attrition, show student** progress and identify students in need (Arnold & Pistilli, 2012; Picciano, 2012; Siemens & Gasevic, 2011). In addition, some studies suggest that student behaviour in an LMS predict academic performance. In their study of nine undergraduate courses in Australia, Gasevic et al. (2014) found that number of logins, resources used and operations performed in discussion forums were significant predictors of academic performance. Despite the positive implications of these findings, there are likely to be moderating variables that impact LMS use and academic performance and the authors note that it is difficult to translate these  findings into actionable recommendations for students (Gasevic et al., 2014). Furthermore, other research has found that LMS use does not predict academic success (Broadbent, 2016). It would be beneficial to further examine how LMS use can be used to assist students.  Despite the advances in technology and relative flexibility of most LMS, one of the major limitations of learning management systems is that they do not lend themselves to learner-centric approaches (Rachman & Dron, 2012). Students are generally not given the opportunity to adapt the LMS to cater to their own learning. Further, the learning analytics offered in the LMS tend to be available to educators but not students. The inability to easily retrieve and adapt data for students in the LMS presents a challenge for the use of learning analytics.  Authors have also noted concerns associated with learning analytics, including the potential to create a culture of student surveillance rather than empowerment (Slade & Prinsloo , 2013). |
| 2 | **Self Efficacy** | Students’ beliefs about their academic capabilities have long been thought to play an important role in their motivation and ability to achieve (Zinmmerman, 1999). In particular, self-reflection and self-efficacy have been found to be important predictors of academic performance. Self-reflection refers to an individual's ability to analyse their own behaviours with outcomes i.e. what actions lead to reactions? Where positive reactions occur, how can we understand and increase the action that led to them? Self-efficacy is an individual's belief that they are likely to succeed in a task (Stajkovic & Luthans, 1979). Students who have higher self-efficacy are more likely to be confident learners and are more likely to participate, engage and persist with their academic studies (Pajares, 2007). Selfefficacy is a strong predictor of academic achievement and success (Broadbent, 2016; Chemers, Hu & Garcia, 2001). It is therefore important to understand ways of improving a student's self-efficacy, but integral to doing this is to have them learn about, and reflect on, their own learning behaviours |
| 46 | **EDM** | Contributions provided by EDM can be classified into categories   * Analysis and visualization of data * Providing feedback for supporting instructors * Recommendations for students * Predicting student performance * Student modeling * Detecting undesirable student behaviors * Grouping students * Social network analysis * Constructing courseware * Developing concept maps * Planning and scheduling |
| 46 | **Learning Style** | Learning Style has been defined by Honey and Mumford [15] as ‘a description of the attitudes and behaviors which determine an individual’s preferred way of learning’. Several studies have proposed different models to explain possi-ble learning styles. Of these models, the FSLSM proposed by Richard Felder and Linda Silverman is well known. It is defined by four dimensions, each formed by a pair of distinct characteris-tics (learning styles)  The first dimension considers the learner’s preferred methodof processing information—active (ACT) or reflective (REF).The second dimension considers the type of information that the learner preferentially perceives—sensory (SEN) or intuitive (INT). The third dimension considers the sensory channel through which the learner most effectively perceives external information—visual (VIS) or verbal (VER). The fourth dimension considers how the learner progresses toward understanding—sequentially (SEQ) or globally (GLO). Interestingly, the ILS developed by Felder and Soloman [16] can be used to assess preferences in four FSLSM dimensions. The ILS comprises 44 questions with 11 questions for each dimension  <https://thepeakperformancecenter.com/educational-learning/learning/preferences/learning-styles/felder-silverman/> |
| 2 | Pedagogical implications associated with LA | LA analytics provide staff with a pedagogical device that can be used in a neutral, formative way to help students become more aware of their own learning and to help understand why they may be facing particular challenges. The potential exists to use learning analytics in the classroom to help students engage in their own learning |
| 2 | LA Application | Learning analytics have tended to be used and viewed from the educator’s perspective. However, there are substantial benefits to directly sharing learning analytics with students (Prinsloo, Slade & Galpin, 2012). Individual pieces of data may not be inherently useful, **but when collected and analysed in cohorts, learning analytics has the power to inform students about how they are progressing, how their learning behaviours compare with other students, as well as information such as learning characteristics of students who are performing** at higher levels. **When given to students and used as a reflective device,** learning analytics may also inform students about how many hours they are spending on learning tasks and how they engage with different types of materials, thus, showing how to maximise learning. Learning analytics can teach students about their own learning behaviours, giving them more insight and agency in their learning |
| 16 | Functions of LMS | Among the top functions and purposes of an LMS are the development, storage, sharing, and management of learning objects, such as student activities, reading materials, portfolios, and performance records. It may also serve as a data bank of examinations and other evaluation tools. LMSs can also be used to generate various records and reports that may aid the schools or organizations to become more effective in delivering of learning process (Yasar & Adiguzel, 2010). With the advent of advanced network technology, the power of Web 2.0 may now be integrated into LMS to promote active interaction not only between students and teachers but also between and among students themselves as well. The vast use of interactive discussion tools such as forums, blogs, wikis, and chat rooms promote collaboration among students via different modalities. LMS can further improve the students’ capacity in constructing new sets of knowledge on their own making them independent learners (Lonn, 2009). In fact, a study conducted by Firat (2016) regarding the effect of LMS learning behavior in the students’ academic performance, stated that “Learning management systems (LMS) have been proven to encourage a constructive approach to knowledge acquisition and to support active learning”. LMS can richly augment the traditional face-to-face classroom set-up by providing a boundless communication between the teachers and the students while allowing the students learn at their own pace (Shulamit &Yossi, 2011). |
| 34 | Goals of LA | There are a multitude of factors that have motivated interest in learning analytics. One motivating factor for the increased interest in learning analytics is the general trend for increased accountability in all levels of education. **Educational institutions around the country are feeling increased pressure to account for what and how their students are learning**. The pressure is even greater on online learning as these courses now have separate standards for accreditation (e.g., Ice et al., 2012). Learning analytics provides one of many methods to not only document student performance but also to provide tools that encourage the types of continuous improvement that accrediting bodies are seeking  On a more national level, institutions of higher education are experiencing greater demands to retain students. For example, the American Graduation Initiative (Brandon, 2009) urges five million additional higher education graduates by 2020. Learning analytics can assist with this goal by providing a more personalized learning experience through the use of data to respond to students’ needs (e.g., Smith, Lange, & Huston, 2012). This kind of personalization will likely lead to greater success in the classroom.  In addition to these national-level interests in learning analytics, there are more local goals that learning analytics address. These can include predicting learner performance, suggesting to learners relevant learning resources, increased reflection and awareness on the part of the learner, detection of undesirable learning behaviors, and detecting affective states (e.g., boredom, frustration) of the learner (Verbert, Manouselis, Drachsler, & Duval, 2012). As mentioned at the outset of this paper, faculty have, for the most part, relied on their intuition and hunches to know when students are struggling, or to know when to suggest relevant learning resources, or to know how to encourage students to reflect on their learning. This intuition and these hunches are not going to disappear with the advent of learning analytics, nor are the actions derived from them. Instead, learning analytics promises to make these hunches and the resulting action more data-driven and easier to detect |
| 34 | LA Data for Prediction | learning analytics is replete with studies on the use of data such as these  to predict student performance. For example, Smith, Lange, and Huston (2012) used such LMS data as login frequency, site engagement, student pace in the course, and assignment grades to predict course outcome. Macfadyen and Dawson (2012) used LMS tool use frequency (e.g.,  number of discussion messages read, number of discussion replies posted) to predict student achievement (course grade). Minaei-Bidgoli, Kashy, Kortemeyer, and Punch (2003) used the number of attempts at doing homework, time spent on a problem, and reading of material to  predict final grades. In an interesting study, Falakmasir and Jafar (2010) examined student performance on activities that affected their final grade. They found that students’ participation in a discussion forum was the best predictor of their final grades.  In a recent study, Dietz-Uhler, Hurn, and Hurn (2012) found that performance on course assignments and tests at various times in the course significantly predicted final grades in an online introductory psychology class. Specifically, they found that performance on the first two exams, a quiz on the syllabus taken before the class started, and assignments in the second half of the course accounted for 98% of the variance in final course grades. With regard to data generated from an LMS, the only variable that significantly predicted final course grade was the number of discussion board posts authored in the second half of the course. These results suggest that it is important to examine performance and behavior indicators at various points in the course in order to help students perform better in the course. Although the amount and type of data faculty likely have available is more accessible and plentiful if using an LMS, there are other types of data that exist and can be mined beyond what is available in an LMS. For example, the widespread use of various technologies, including email, text messages, and social networks, make the amount and type of data more widespread and easier to mine (Long & Siemens, 2011). |
| 34 | LA Concerns | Pedagogy should drive learning analytics and not necessarily the converse (Greller & Drachsler, 2012). Campbell et al. (2007) provide a list of the issues and concerns that must be addressed before implementing any program or course of action on learning analytics.  Some of these concerns include:   * Big brother: It may be threatening to some students and faculty to know that someone can “watch” and track all that they do. * Holistic view: There is a concern that any data set, no matter how comprehensive, cannot take into account other issues, such as interpersonal ones. * Faculty involvement: Faculty need to be involved in order for learning analytics to have its greatest impact. * Obligation to act: Are faculty and institutions obligated to use data to increase the probability of student success?   In an interesting article on the potential harmful effects of learning analytics, Dringus (2012) argues that learning analytics (in online courses), must get meaningful data, have transparency, yield good algorithms, lead to effective use of the data, and inform process and practice. Without attending to these minimal requirements, Dringus argues that learning analytics can be harmful. Other issues that are frequently highlighted in discussions of learning analytics include profiling and how learning-analytics data will be used. Specifically, there is a danger of creating.  a profile of successful and unsuccessful students. More importantly, there is concern that a profile creates a set of expectations for the student and faculty (Campbell et al., 2007). Of course, students and faculty already have expectations – the issue is that learning analytics might add a set of data-driven expectations.  Data privacy and the use of data are also strong concerns of the use of learning analytics. There are legal and ethical issues, such as FERPA, that need to be addressed before faculty or institutions can make use of some student data (Campbell et al., 2007; Greller & Drachsler, 2012). Similarly, there is the issue of who the data belong to. Once the data have been warehoused, can anyone have access to it (Campbell et al., 2007; Greller & Drachsler, 2012)? Finally, there is the issue of whether or not we are really measuring student learning, or are we just attempting to boost student retention and course completion (Watters, 2012). If one considers the types of data that are mined for learning analytics, such as the number of course tools accessed in an LMS, or the number of posts “read” on the discussion forum, are these really proxies for learning? This is not to suggest that learning analytics cannot boost learning, but we need to be clear about what we are measuring and predicting |
| 27 | LA vs Survey | Learning Analytics, have made fulfilling this requirement possible. Since most of learners activities take place in the LMS, Learning Analytics tools can potentially utilize log data to provide crucial information on how learning processes occur throughout the login duration (Jo et al., 2014). Consequently, they can provide institutions informed decisions about possible problems related to students’ learning (Kotsiantis et al., 2013; Phillips et al., 2011). Compared with subjective methods such as surveys and questionnaires, Learning Analytics can capture learners’ authentic interactions in real time. |
| 27 | LMS data | LMS accumulate vast amounts of data on student behavior that can be used to inform and improve student engagement in LMS (Beer et al., 2010). These information include users visits, number of downloads, LMS tools accessed, messages read or posted, and content pages visited (Macfadyen & Dawson, 2010). According to Whitmer (2012), **such information explain over four times the variation in final grades compared to traditional student characteristic variables, and that combining both types of variables increase the quality of predicting learning performance by more than 70%**  Therefore, through analyzing LMS usage via log data we can understand the status of students’ learning and even predict their possible learning achievement (Yu & Jo, 2014). In this case, we can **identify struggling students in need of academic suppor**t (Macfadyen & Dawson, 2010). We can also use Learning Analytics tools to  **assess the quality of online postings** (Nistor et al., 2015) and visualize usage behaviors in the system (Scheffel et al., 2011). Given the benefits and opportunities offered by log data stored in LMS database, studies have developed various Learning Analytics tools to analyze such data. For instance, Yu and Jo (2014)  **studied factors that influence students’ academic achievement using log data collected from Moodle** with 84 students in a university in South Korea. They found that **total studying time, interaction with peers, regularity of learning interval, and number of downloads had a significant effect on students’ academic performance in online learning environment.** |
| 34 | LA types | May (2011) suggests that learning analytics can be both descriptive and predictive. From a descriptive perspective, learning analytics can help us answer such questions as:  “What happened?”, “Where was the problem?”, and “What actions are needed?”.  Learning analytics can also help us to predict and prescribe by answering such questions as: “Why is this happening?”, “What if these trends continue?”, “What will happen next?”, and “What is the best that can  happen?”.  This approach is also consistent with the five stages of the use of learning analytics in higher education suggested by Goldstein and Katz (2005): data extraction, performance analysis, what-if decision support, predictive modeling, and automatic response triggers. |
| 35 | LA | Analysis of LMS data is often referred to as LA |

## T12 LA : Applications/ Benefits

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| --- | --- | --- |
| pID | subject | description |
| 34 | LA Benefits | Among these are to improve student success, increase retention, and improve accountability. But as an individual faculty member, why might you want to make use of learning analytics on a smaller, course-level scale?  education. Several of these benefits are focused on an administrative level, such as improving decision-making and informing resource allocation, highlighting an institution’s successes and challenges, and increasing organizational productivity. From the perspective of a faculty member, they suggest that learning analytics can help faculty identify at-risk learners and provide interventions, transform pedagogical approaches, and help students gain insight into their own learning. Having data at hand and knowing what to do with it can allow us to realize these benefits. For example, if we learn (from a correlational analysis) that student performance on certain activities is not related to final grades, then we might consider modifying these activities. Similarly, we can use data from an LMS to build a model of successful student behaviors, which might include the frequency of LMS tool use, frequency of accessing discussion board posts, and the number of times taking quizzes. If we can build a model of successful student behaviors, then we can encourage (with data!) our students to engage in these behaviors. Alternatively, we can also identify at-risk students as ones who deviate from this model. Likewise, Greller and Drachsler (2012) suggest that learning analytics can help faculty by informing them of the gaps in knowledge displayed by their students. Understanding these knowledge gaps can help faculty focus their attention on particular students or pieces of information. Of course, for institutions such as Purdue or Rio Salado that have performance dashboards in their LMSs, students can constantly monitor their progress and determine how they are performing, so there are benefits at the student level as well. |
| 34 | LA Benefits | Among these are to improve student success, increase retention, and improve accountability. But as an individual faculty member, why might you want to make use of learning analytics on a smaller, course-level scale?  education. Several of these benefits are focused on an administrative level, such as improving decision-making and informing resource allocation, highlighting an institution’s successes and challenges, and increasing organizational productivity. From the perspective of a faculty member, they suggest that learning analytics can help faculty identify at-risk learners and provide interventions, transform pedagogical approaches, and help students gain insight into their own learning. Having data at hand and knowing what to do with it can allow us to realize these benefits. For example, if we learn (from a correlational analysis) that student performance on certain activities is not related to final grades, then we might consider modifying these activities. Similarly, we can use data from an LMS to build a model of successful student behaviors, which might include the frequency of LMS tool use, frequency of accessing discussion board posts, and the number of times taking quizzes. If we can build a model of successful student behaviors, then we can encourage (with data!) our students to engage in these behaviors. Alternatively, we can also identify at-risk students as ones who deviate from this model. Likewise, Greller and Drachsler (2012) suggest that learning analytics can help faculty by informing them of the gaps in knowledge displayed by their students. Understanding these knowledge gaps can help faculty focus their attention on particular students or pieces of information. Of course, for institutions such as Purdue or Rio Salado that have performance dashboards in their LMSs, students can constantly monitor their progress and determine how they are performing, so there are benefits at the student level as well. |
| 34 | LA for teachers | Learning analytics can help faculty improve teaching and learning opportunities for students (Hrabowski, Suess, & Fritz, 2011; Mattingly, Rice, & Berg, 2012). By monitoring student performance and participation in a course, as well as examining how this relates to grades, faculty can potentially spot areas of the course to improve. Such improvements in the course allow for the continual improvements that accrediting bodies are recommending. In an interesting white paper, IBM (2001) suggests ways in which educational institutions can help improve student achievement.  These include:   * Monitoring individual student performance * Disaggregating student performance by selected characteristics such as major,year of study, ethnicity, etc. * Identifying outliers for early intervention * Predicting potential so that all students achieve optimally * Preventing attrition from a course or program * Identifying and developing effective instructional techniques * Analyzing standard assessment techniques and instruments * Testing and evaluation of curricula |
| 34 | LA for students | learning analytics can be used to help students succeed and to  improve retention. Learning analytics can provide insights into what is happening with the learner in nearly real-time. Armed with this information, faculty can make suggestions to students that will help them succeed (Long & Siemens, 2011). For example, if a student has not  Journal of Interactive Online Learning Dietz-Uhler & Hurn 22 read a discussion board post for a certain period of time, this may suggest to an instructor that the student needs an intervention or a nudge. Similarly, if a typically successful student suddenly performs poorly on an assignment, the instructor can intervene and seek to determine why the student performed poorly. Or, if a student repeatedly asks questions about the material or about course procedures, an instructor can examine usage data in an LMS and determine if, when, and how often the student has accessed the relevant LMS tools. |