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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** | **Learner Analytics to Predict Performance of Learners in LMS** |
| **Problem Statement** | E-Learning is rapidly evolving field which is capturing more and more data about learners. The study conducted on latest LMS will provide greater knowledge in predicting Performance among Learners than earlier researches. 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 |

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# 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** |  |

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# Templates

## T6 - Template with Sample Data

|  |  |  |
| --- | --- | --- |
| ser | **subject** | description |
| 1.1 | **serial** | 0 |
| 1.2 | **dateA** | Date Added into this Biblio : 01-Jan-20 |
| 1.3 | **dateR** | Date Read : 01-Jan-20 |
| 1.4 | **rating** | Rate the paper Quality 0 - 10 |
| 2.2 | **title** | Title of the paper |
| 2.3 | **area** | PM/LA/EDM/LMS |
| 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 |
| 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 | **refPID** | Referred Paper ID in this document |

## T7 - Blank Template

|  |  |  |
| --- | --- | --- |
| ser | **subject** | description |
| 1.1 | **serial** |  |
| 1.2 | **dateA** |  |
| 1.3 | **dateR** |  |
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| 2.2 | **title** |  |
| 2.3 | **area** |  |
| 2.4 | **authors** |  |
| 2.4 | **year** |  |
| 2.5 | **publication** |  |
| 2.6 | **type** |  |
| 3.1 | **link1** |  |
| 3.2 | **link2** |  |
| 3.3 | **citEEE** |  |
| 3.4 | **citAPA** |  |
| 3.5 | **citOthers** |  |
| 4.1 | **keywords** |  |
| 4.2 | **abstract** |  |
| 4.3 | **chapters** |  |
| 4.3 | **tags** |  |
| 5.1 | **RQ** |  |
| 5.2 | **RO** |  |
| 5.3 | **points** |  |
| 5.4 | **data** |  |
| 5.5. | **factors** |  |
| 5.6 | **methods** |  |
| 5.7 | **results** |  |
| 5.8 | **conclusion** |  |
| 5.9 | **limitations** |  |
| 6.1 | **futurework** |  |
| 6.2 | **gaps** |  |
| 6.3 | **comments** |  |
| 6.4 | **myres** |  |
| 6.5 | **guide** |  |
| 6,6 | **refPID** |  |

## T8 - Blank Table

|  |  |  |
| --- | --- | --- |
| ser | subject | description |
| 1.1 | serial |  |
|  |  |  |

## T9 - Blank Table

|  |  |  |
| --- | --- | --- |
| ser | **subject** | description |
| 1.1 | **serial** |  |
| 2.2 | **title** |  |
| 2.3 | **area** |  |
| 2.4 | **authors** |  |
| 2.4 | **year** |  |
| 2.5 | **publication** |  |
| 5.7 | **results** |  |
| 5.8 | **conclusion** |  |
| 6.1 | **futurework** |  |
| 6.2 | **gaps** |  |

## T10 - Blank Table

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| 1.1 | **serial** |  |

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# Papers

## T11-1 - Factors influencing beliefs for adoption of a learning analytics tool: An empirical study.

|  |  |  |
| --- | --- | --- |
| ser | **subject** | description |
| 1.1 | **serial** | 1 |
| 1.2 | **dateA** |  |
| 1.3 | **dateR** |  |
| 1.4 | **rating** | 5 |
| 2.2 | **title** | Factors influencing beliefs for adoption of a learning analytics tool: An empirical study. |
| 2.3 | **area** |  |
| 2.4 | **authors** | **Ali, L., Asadi, M., Gaševic, D., Jovanovic, J., & Hatala, M. (2013)** |
| 2.4 | **year** | 2013 |
| 2.5 | **publication** | Computers & Education, 62, 130-148. doi:10.1016/j.compedu.2012.10.023 |
| 2.6 | **type** |  |
| 3.1 | **link1** |  |
| 3.2 | **link2** |  |
| 3.3 | **citEEE** |  |
| 3.4 | **citAPA** |  |
| 4.1 | **keywords** |  |
| 4.2 | **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 , |
| 4.3 | **chapters** |  |
| 4.3 | **tags** |  |
| 5.1 | **RQ** |  |
| 5.2 | **RO** |  |
| 5.5. | **factors** |  |
| 5.6 | **methods** |  |
| 5.7 | **results** |  |
| 5.8 | **conclusion** |  |
| 6.1 | **futurework** |  |
| 6.2 | **gaps** |  |
| 6.3 | **comments** | 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. |
| 6.4 | **myres** |  |
| 6.5 | **guide** |  |

## T12-2 - Factors influencing beliefs for adoption of a learning analytics tool: An empirical study.

|  |  |  |
| --- | --- | --- |
| ser | **subject** | description |
| 1.1 | **serial** | 2 |
| 1.2 | **dateA** |  |
| 1.3 | **dateR** |  |
| 1.4 | **rating** |  |
| 2.2 | **title** | Factors influencing beliefs for adoption of a learning analytics tool: An empirical study. |
| 2.3 | **area** |  |
| 2.4 | **authors** |  |
| 2.4 | **year** |  |
| 2.5 | **publication** |  |
| 2.6 | **type** |  |
| 3.1 | **link1** |  |
| 3.2 | **link2** |  |
| 3.3 | **citEEE** |  |
| 3.4 | **citAPA** |  |
| 4.1 | **keywords** |  |
| 4.2 | **abstract** |  |
| 4.3 | **chapters** |  |
| 4.3 | **tags** |  |
| 5.1 | **RQ** |  |
| 5.2 | **RO** |  |
| 5.5. | **factors** |  |
| 5.6 | **methods** |  |
| 5.7 | **results** |  |
| 5.8 | **conclusion** |  |
| 6.1 | **futurework** |  |
| 6.2 | **gaps** |  |
| 6.3 | **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. |
| 6.4 | **myres** |  |
| 6.5 | **guide** |  |

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

## student success.

|  |  |  |
| --- | --- | --- |
| ser | **subject** | description |
| 1.1 | **serial** | 3 |
| 1.2 | **dateA** |  |
| 1.3 | **dateR** |  |
| 1.4 | **rating** |  |
| 2.2 | **title** | Course Signals at Purdue: Using learning analytics to increase  student success |
| 2.3 | **area** |  |
| 2.4 | **authors** | **Arnold, K. E. & Pistilli, M. D. (2012).** |
| 2.4 | **year** |  |
| 2.5 | **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 |
| 2.6 | **type** |  |
| 3.1 | **link1** |  |
| 3.2 | **link2** |  |
| 3.3 | **citEEE** |  |
| 3.4 | **citAPA** |  |
| 4.1 | **keywords** |  |
| 4.2 | **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. |
| 4.3 | **chapters** |  |
| 4.3 | **tags** |  |
| 5.1 | **RQ** |  |
| 5.2 | **RO** |  |
| 5.5. | **factors** |  |
| 5.6 | **methods** |  |
| 5.7 | **results** |  |
| 5.8 | **conclusion** |  |
| 6.1 | **futurework** |  |
| 6.2 | **gaps** |  |
| 6.3 | **comments** |  |
| 6.4 | **myres** |  |
| 6.5 | **guide** |  |

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

|  |  |  |
| --- | --- | --- |
| ser | **subject** | description |
| 1.1 | **serial** | 4 |
| 1.2 | **dateA** |  |
| 1.3 | **dateR** |  |
| 1.4 | **rating** |  |
| 2.2 | **title** | Educational Data Mining & Students’ Performance Prediction |
| 2.3 | **area** |  |
| 2.4 | **authors** |  |
| 2.4 | **year** |  |
| 2.5 | **publication** |  |
| 2.6 | **type** |  |
| 3.1 | **link1** |  |
| 3.2 | **link2** | <https://thesai.org/Downloads/Volume7No5/Paper_31-Educational_Data_Mining_Students_Performance_Prediction.pdf> |
| 3.3 | **citEEE** |  |
| 3.4 | **citAPA** |  |
| 4.1 | **keywords** |  |
| 4.2 | **abstract** |  |
| 4.3 | **chapters** |  |
| 4.3 | **tags** |  |
| 5.1 | **RQ** |  |
| 5.2 | **RO** |  |
| 5.5. | **factors** |  |
| 5.6 | **methods** |  |
| 5.7 | **results** |  |
| 5.8 | **conclusion** |  |
| 6.1 | **futurework** |  |
| 6.2 | **gaps** |  |
| 6.3 | **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. |
| 6.4 | **myres** |  |
| 6.5 | **guide** |  |

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

|  |  |  |
| --- | --- | --- |
| ser | **subject** | description |
| 1.1 | **serial** | 5 |
| 1.2 | **dateA** |  |
| 1.3 | **dateR** |  |
| 1.4 | **rating** |  |
| 2.2 | **title** | Machine Learning Approaches to Predict Learning Outcomes in Massive Open Learning Courses |
| 2.3 | **area** |  |
| 2.4 | **authors** |  |
| 2.4 | **year** |  |
| 2.5 | **publication** |  |
| 2.6 | **type** |  |
| 3.1 | **link1** |  |
| 3.2 | **link2** |  |
| 3.3 | **citEEE** |  |
| 3.4 | **citAPA** |  |
| 4.1 | **keywords** |  |
| 4.2 | **abstract** |  |
| 4.3 | **chapters** |  |
| 4.3 | **tags** |  |
| 5.1 | **RQ** |  |
| 5.2 | **RO** |  |
| 5.5. | **factors** |  |
| 5.6 | **methods** |  |
| 5.7 | **results** |  |
| 5.8 | **conclusion** |  |
| 6.1 | **futurework** |  |
| 6.2 | **gaps** |  |
| 6.3 | **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. |
| 6.4 | **myres** |  |
| 6.5 | **guide** |  |

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

|  |  |  |
| --- | --- | --- |
| ser | **subject** | description |
| 1.1 | **serial** | 6 |
| 1.2 | **dateA** |  |
| 1.3 | **dateR** |  |
| 1.4 | **rating** |  |
| 2.2 | **title** | Learning Analytic in a Smart Classroom to Improve eEducation |
| 2.3 | **area** |  |
| 2.4 | **authors** |  |
| 2.4 | **year** |  |
| 2.5 | **publication** |  |
| 2.6 | **type** |  |
| 3.1 | **link1** | http://ieeexplore.ieee.org/document/7962510/ |
| 3.2 | **link2** |  |
| 3.3 | **citEEE** |  |
| 3.4 | **citAPA** |  |
| 4.1 | **keywords** |  |
| 4.2 | **abstract** |  |
| 4.3 | **chapters** |  |
| 4.3 | **tags** |  |
| 5.1 | **RQ** |  |
| 5.2 | **RO** |  |
| 5.5. | **factors** |  |
| 5.6 | **methods** |  |
| 5.7 | **results** |  |
| 5.8 | **conclusion** |  |
| 6.1 | **futurework** |  |
| 6.2 | **gaps** |  |
| 6.3 | **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 |
| 6.4 | **myres** |  |
| 6.5 | **guide** |  |

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

|  |  |  |
| --- | --- | --- |
| ser | **subject** | description |
| 1.1 | **serial** | 7 |
| 1.2 | **dateA** |  |
| 1.3 | **dateR** |  |
| 1.4 | **rating** |  |
| 2.2 | **title** | Big Data and analytics in higher education: Opportunities and challenges |
| 2.3 | **area** |  |
| 2.4 | **authors** | Ben Daniel |
| 2.4 | **year** | 2014 |
| 2.5 | **publication** | British Journal of Edn Technology |
| 2.6 | **type** |  |
| 3.1 | **link1** |  |
| 3.2 | **link2** |  |
| 3.3 | **citEEE** |  |
| 3.4 | **citAPA** |  |
| 4.1 | **keywords** |  |
| 4.2 | **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. |
| 4.3 | **chapters** |  |
| 4.3 | **tags** |  |
| 5.1 | **RQ** |  |
| 5.2 | **RO** |  |
| 5.5. | **factors** |  |
| 5.6 | **methods** |  |
| 5.7 | **results** |  |
| 5.8 | **conclusion** |  |
| 6.1 | **futurework** |  |
| 6.2 | **gaps** |  |
| 6.3 | **comments** |  |
| 6.4 | **myres** |  |
| 6.5 | **guide** |  |

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

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| --- | --- | --- |
| ser | **subject** | description |
| 1.1 | **serial** | 8 |
| 1.2 | **dateA** |  |
| 1.3 | **dateR** |  |
| 1.4 | **rating** |  |
| 2.2 | **title** | Comparative Analysis of the Effect of Attendance on Academic Performance of Management and Finance Course Students |
| 2.3 | **area** |  |
| 2.4 | **authors** |  |
| 2.4 | **year** |  |
| 2.5 | **publication** |  |
| 2.6 | **type** |  |
| 3.1 | **link1** |  |
| 3.2 | **link2** |  |
| 3.3 | **citEEE** |  |
| 3.4 | **citAPA** |  |
| 4.1 | **keywords** | Academic Performance Attendance Teacher-Student Interaction Personality |
| 4.2 | **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. |
| 4.3 | **chapters** |  |
| 4.3 | **tags** |  |
| 5.1 | **RQ** |  |
| 5.2 | **RO** |  |
| 5.5. | **factors** |  |
| 5.6 | **methods** |  |
| 5.7 | **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. |
| 5.8 | **conclusion** |  |
| 6.1 | **futurework** |  |
| 6.2 | **gaps** |  |
| 6.3 | **comments** |  |
| 6.4 | **myres** |  |
| 6.5 | **guide** |  |

## 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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| ser | **subject** | description |
| 1.1 | **serial** | 9 |
| 1.2 | **dateA** |  |
| 1.3 | **dateR** |  |
| 1.4 | **rating** |  |
| 2.2 | **title** | An analysis of some factors affecting student academic performance in an introductory biochemistry course at the University of the West Indies |
| 2.3 | **area** |  |
| 2.4 | **authors** |  |
| 2.4 | **year** |  |
| 2.5 | **publication** |  |
| 2.6 | **type** |  |
| 3.1 | **link1** |  |
| 3.2 | **link2** |  |
| 3.3 | **citEEE** |  |
| 3.4 | **citAPA** |  |
| 4.1 | **keywords** | high failure rates, introductory biochemistry, learning preferences, mature students, gender, entry qualifications. |
| 4.2 | **abstract** |  |
| 4.3 | **chapters** |  |
| 4.3 | **tags** |  |
| 5.1 | **RQ** |  |
| 5.2 | **RO** |  |
| 5.5. | **factors** |  |
| 5.6 | **methods** |  |
| 5.7 | **results** |  |
| 5.8 | **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. |
| 6.1 | **futurework** |  |
| 6.2 | **gaps** |  |
| 6.3 | **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 |
| 6.4 | **myres** |  |
| 6.5 | **guide** |  |

## 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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| --- | --- | --- |
| ser | subject | description |
| 1.1 | serial | 10 |
| 1.4 | rating |  |
| 2.2 | title | An analysis of some factors affecting student academic performance in an introductory biochemistry course at the University of the West Indies |
| 4.2 | 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. |
| 5.7 | 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. |
| 6.3 | 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

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| --- | --- | --- |
| ser | subject | description |
| 1.1 | serial | 11 |
| 1.4 | rating |  |
| 4.1 | keywords | Regression with multi-regression models, Analyzing student behavior, Predicting student performance |
| 2.2 | title | Personalized Multi-Regression Models for Predicting Students’ Performance in Course Activities |
| 4.2 | 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. |
| 6.3 | 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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| ser | subject | description |
| 1.1 | serial | 12 |
| 2.2 | title | Applying Web-Mining Methods for Analysis of Student Behaviour in VLE Courses |
| 4.1 | keywords | virtual learning environment, collaborative learning, constructivist pedagogy, web-mining method |
| 4.2 | 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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| ser | subject | description |
| 1.1 | serial | 13 |
| 2.2 | title | An Educational Data Mining Model for Predicting Student Performance in Programming Course |
| 4.1 | keywords | Data Mining, Student Performance, Programming Course, Rule Extraction. |
| 4.2 | 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. |
| 5.8 | 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

|  |  |  |
| --- | --- | --- |
| ser | subject | description |
| 1.1 | serial | 14 |
| 2.2 | title | Factorization Models for Forecasting Student Performance |
| 4.2 | 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. |
| 6.3 | 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 - Mining Educational Data to Predict Students Academic Performance using Ensemble Methods

|  |  |  |
| --- | --- | --- |
| ser | subject | description |
| 1.1 | serial | 15 |
| 2.4 | year | 2005 |
| 2.2 | area | LA |
| 2.2 | title | Mining Educational Data to Predict Students Academic Performance using Ensemble Methods |

## T26-16 - Web usage Mining for Predicting Final Marks of Students that use Moodle Courses

|  |  |  |
| --- | --- | --- |
| **ser** | **subject** | **description** |
| 1.1 | serial | 16 |
| 2.4 | year | 2010 |
| 5.6 | methods | Classification, Decision Tree |
| 3.1 | link1 | <https://www.researchgate.net/publication/229891919_Web_usage_mining_for_predicting_marks_of_students_that_use_Moodle_courses> |
| 2.2 | area | PM |
| 2.2 | title | Web usage Mining for Predicting Final Marks of Students that use Moodle Courses |

## T27-17 Title : Performance Analysis and Prediction in Educational

## Data Mining: A Research Travelogue

|  |  |  |
| --- | --- | --- |
| **ser** | **subject** | **description** |
| 1.1 | serial | 17 |
| 2.4 | year | 2015 |
| 5.5 | factors | As per Paper |
| 5.2 | RO | comprehensive survey, a travelogue (2002-2014) towards educational data mining and its scope in future |
| 5.6 | methods | Different |
| 5.4 | data | Different |
| 3.1 | link1 | <https://research.ijcaonline.org/volume110/number15/pxc3901007.pdf> |
| 6.1 | 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). |
| 2.2 | title | Performance Analysis and Prediction in Educational  Data Mining: A Research Travelogue |
| 2.2 | area | PM |
| 5.1 | 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 |
| 5.7 | results | There is a clear need for unified approach |
| 2.4 | authors |  |

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

|  |  |  |
| --- | --- | --- |
| **ser** | **subject** | **description** |
| 1.1 | serial | 18 |
| 2.4 | year | 2015 |
| 2.2 | title | Factors affecting students completion : study of online Masters Program |
| 2.2 | area | LA |
| 5.5 | factors |  |

## T29-19 - EDM & students performance prediction

|  |  |  |
| --- | --- | --- |
| **ser** | **subject** | **description** |
| 2.2 | area | LA |
| 2.2 | title | EDM & students performance prediction |
| 2.4 | year | 2016 |
| 1.1 | serial | 19 |

## T30-20 Title : Indicators of Good Student Performance in Moodle Activity Data

|  |  |  |
| --- | --- | --- |
| **ser** | **subject** | **description** |
| 1.1 | serial | 20 |
| 2.4 | year | 2016 |
| 5.2 | RO | analysis of Moodle activity data focusedon identifying early predictors of good student performance |
| 5.1 | RQ | early submission is a good sign, a high level of activityis predictive of good results and evening activity is even bet-ter than daytime activity. |
| 5.5 | factors | Grades, Assignment Submissions, Logs |
| 3.1 | link1 | <https://www.researchgate.net/publication/290527303_Indicators_of_Good_Student_Performance_in_Moodle_Activity_Data> |
| 6.1 | futurework | Identifying Outliers |
| 2.2 | title | Indicators of Good Student Performance in Moodle Activity Data |
| 5.4 | data | Logs, Moodle Data |
| 2.2 | area | PM |
| 5.6 | methods | Table, Statistics, Visualisaiton |
| 5.7 | results |  |
| 2.4 | authors |  |

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

|  |  |  |
| --- | --- | --- |
| **ser** | **subject** | **description** |
| 1.1 | serial | 21 |
| 2.4 | year | 2016 |
| 2.2 | title | Discovering Students use of Learning Resources with EDM |
| 2.2 | area | LA |
| 5.2 | RO |  |

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

|  |  |  |
| --- | --- | --- |
| **ser** | **subject** | **description** |
| 1.1 | serial | 22 |
| 2.4 | year | 2016 |
| 2.2 | title | Framework for LA in Moodle for assessing Course Outcomes |
| 2.2 | area | LA |
| 5.2 | RO |  |

## T33-23 Title: Predicting Grades

|  |  |  |
| --- | --- | --- |
| **ser** | **subject** | **description** |
| 1.1 | serial | 23 |
| 2.4 | year | 2016 |
| 2.2 | area | LA |
| 2.2 | title | Predicting Grades |

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

|  |  |  |
| --- | --- | --- |
| **ser** | **subject** | **description** |
| 1.1 | serial | 24 |
| 2.4 | year | 2016 |
| 2.2 | title | EDM & students performance prediction |
| 2.2 | area | LA |

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

|  |  |  |
| --- | --- | --- |
| **ser** | **subject** | **description** |
| 1.1 | serial | 25 |
| 2.4 | year | 2017 |
| 2.2 | title | Finding Key Integer Values in Many Features for Learners Academic Performance Prediction |
| 2.2 | area | LA |

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

|  |  |  |
| --- | --- | --- |
| **ser** | **subject** | **description** |
| 1.1 | serial | 26 |
| 2.4 | year | 2017 |
| 2.2 | title | Predicting Students performance based on Learning Style byu using ANN |
| 2.2 | area | LA |

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

|  |  |  |
| --- | --- | --- |
| **ser** | **subject** | **description** |
| 1.1 | serial | 27 |
| 2.4 | year | 2017 |
| 2.2 | title | Using Learning Analytics to Predict Students Performance in Moodle LMS : Case of Mbeya University of Science & Technology |
| 2.2 | area | LA |

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

|  |  |  |
| --- | --- | --- |
| **ser** | **subject** | **description** |
| 1.1 | serial | 28 |
| 2.4 | year | 2017 |
| 6.1 | futurework | Clustering of learning material, optimal sequence |
| 5.6 | methods | Clustering, Linear Regression |
| 5.5 | factors | Counts of scolls, time between events & various assessment scores, per session test |
| 2.2 | title | Educational DM & Data Analysis for optimal Learning Content Management |
| 2.2 | area | LA |
| 5.7 | results | TBA / Session Lengths follow Log normal & exponential distributions |
| 5.2 | RO | Time Between Actions (TBA) |
| 5.1 | RQ | Whether TBA follows any PDF & if so which one. Whether paramters of such PDF serve as features for the clustering |
| 3.1 | link1 |  |
| 5.4 | data |  |
| 2.4 | authors |  |

## T39-29 Title: EDM & Learning Analysis

|  |  |  |
| --- | --- | --- |
| **ser** | **subject** | **description** |
| 1.1 | serial | 29 |
| 2.4 | year | 2017 |
| 5.6 | methods | Clustering |
| 2.2 | title | EDM & Learning Analysis |
| 2.2 | area | LA |
| 5.4 | data | log |
| 5.5 | 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

|  |  |  |
| --- | --- | --- |
| **ser** | **subject** | **description** |
| 1.1 | serial | 30 |
| 2.4 | year | 2017 |
| 2.2 | area | LA |
| 2.2 | title | Review of EDM Techniques & Recommendation model in analysing Student performance |

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

|  |  |  |
| --- | --- | --- |
| **ser** | **subject** | **description** |
| 1.1 | serial | 31 |
| 2.4 | year | 2017 |
| 2.2 | area | LA |
| 2.2 | title | A survey of EDM research |

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

|  |  |  |
| --- | --- | --- |
| **ser** | **subject** | **description** |
| 1.1 | serial | 32 |
| 2.4 | year | 2018 |
| 2.2 | area | LA |
| 2.2 | title | A LA approach for student performance assessment |

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

|  |  |  |
| --- | --- | --- |
| **ser** | **subject** | **description** |
| 1.1 | serial | 33 |
| 2.4 | year | 2018 |
| 2.2 | area | LA |
| 2.2 | title | A literature review of empirical research on learning analytics in medical education |

## T44-34 Title: Analysis of Student Behavior and Success Based on Logs in Moodle

|  |  |  |
| --- | --- | --- |
| **ser** | **subject** | **description** |
| 1.1 | serial | 34 |
| 2.4 | year | 2018 |
| 2.2 | title | Analysis of Student Behavior and Success Based on Logs in Moodle |
| 5.7 | results | Different |
| 5.5 | factors | Final Grades, Events |
| 3.1 | link1 | <https://bib.irb.hr/datoteka/939844.ce_31_48061.pdf> |
| 5.4 | data | Logs, Grades |
| 6.1 | futurework | More Courses & Disciplines |
| 2.2 | area | PM |
| 5.1 | 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? |
| 5.2 | RO | Relationship of Activity on Grades |
| 5.6 | methods | Visualisation; Statistics |
| 2.4 | 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. |
| 5.3 | 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 is 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, the 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 |

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

|  |  |  |
| --- | --- | --- |
| **ser** | **subject** | **description** |
| 1.1 | serial | 35 |
| 2.4 | year | 2018 |
| 2.2 | title | Can we Predict Student Learning Performance from LMS Data ? A Classification approach |
| 2.2 | area | LA |

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

|  |  |  |
| --- | --- | --- |
| **ser** | **subject** | **description** |
| 1.1 | serial | 36 |
| 2.4 | year | 2018 |
| 2.2 | title | Data mining in course management systems: Moodle case study and tutorial |
| 3.1 | link1 | <https://www.academia.edu/2400757/Data_mining_in_course_management_systems_Moodle_case_study_and_tutorial> |
| 2.2 | area | PM |

## T47-37 Title: Improving Student Performance through Gamification - A user study

|  |  |  |
| --- | --- | --- |
| **ser** | **subject** | **description** |
| 1.1 | serial | 37 |
| 2.4 | year | 2018 |
| 2.2 | area | GBL |
| 2.2 | title | Improving Student Performance through Gamification - A user study |

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

|  |  |  |
| --- | --- | --- |
| **ser** | **subject** | **description** |
| 1.1 | serial | 38 |
| 2.4 | year | 2018 |
| 2.2 | area | LA |
| 2.2 | title | Student Engagement Predictions in an e-Learning Systems and their Impact on Student Course Assessment Scores |

## T49-39 Title: The effects of gamification elements in e-learning platforms

|  |  |  |
| --- | --- | --- |
| **ser** | **subject** | **description** |
| 1.1 | serial | 39 |
| 2.4 | year | 2018 |
| 2.2 | area | GBL |
| 2.2 | title | The effects of gamification elements in e-learning platforms |

## T50-40 Title: Prediction of Student Success Through Analysis of Moodle Logs : Case Study

|  |  |  |
| --- | --- | --- |
| **ser** | **subject** | **description** |
| 1.1 | serial | 40 |
| 2.4 | year | 2019 |
| 2.2 | area | PM |
| 2.2 | title | Prediction of Student Success Through Analysis of Moodle Logs : Case Study |
| 3.1 | link1 | <https://bib.irb.hr/datoteka/939844.ce_31_48061.pdf> |

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

|  |  |  |
| --- | --- | --- |
| **ser** | **subject** | **description** |
| 1.1 | serial | 41 |
| 2.4 | year | 2020 |
| 2.2 | area | LA |
| 2.2 | title | LA Challenges : Trade-offs, Methodology, Scalability |

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

|  |  |  |
| --- | --- | --- |
| **ser** | **subject** | **description** |
| 1.1 | serial | 42 |
| 2.4 | year | 2020 |
| 2.2 | area | LA |
| 2.2 | title | Prediction of student academic performance using Moodle Data from a Further Education setting |

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

|  |  |  |
| --- | --- | --- |
| **ser** | **subject** | **description** |
| 1.1 | serial | 43 |
| 2.4 | year |  |
| 2.2 | area | LA |
| 2.2 | title | Analysing Performance of Students by using DM techniques (LR) |

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

|  |  |  |
| --- | --- | --- |
| **ser** | **subject** | **description** |
| 1.1 | serial | 44 |
| 2.4 | year |  |
| 2.2 | area | LA |
| 2.2 | title | Comparing the factors that predict completion & grades among for Credit & open/ MOOC students in online learning |

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

|  |  |  |
| --- | --- | --- |
| **ser** | **subject** | **description** |
| 1.1 | serial | 45 |
| 2.4 | year |  |
| 2.2 | area | LA |
| 2.2 | title | Comparison of 17 Blended Courses using Moodle LMS |

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

|  |  |  |
| --- | --- | --- |
| **ser** | **subject** | **description** |
| 1.1 | serial | 46 |
| 2.4 | year |  |
| 2.2 | area | LA |
| 2.2 | title | Detecting Learning Styles in Learning Management Using Data Mining |

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

|  |  |  |
| --- | --- | --- |
| **ser** | **subject** | **description** |
| 1.1 | serial | 47 |
| 2.4 | year |  |
| 2.2 | area | LA |
| 2.2 | title | E-learning : Challenges & Research opportunities using ML & Data Analytics |

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

|  |  |  |
| --- | --- | --- |
| **ser** | **subject** | **description** |
| 1.1 | serial | 48 |
| 2.4 | year |  |
| 2.2 | area | LA |
| 2.2 | title | EDM & data analysis for optimal learning content management |

## T59-49 Title: Gamification in e-learning : A Moodle implementation & its effect on student engagement & performance

|  |  |  |
| --- | --- | --- |
| **ser** | **subject** | **description** |
| 1.1 | serial | 49 |
| 2.4 | year |  |
| 2.2 | area | GBL |
| 2.2 | title | Gamification in e-learning : A Moodle implementation & its effect on student engagement & performance |

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

|  |  |  |
| --- | --- | --- |
| **ser** | **subject** | **description** |
| 1.1 | serial | 50 |
| 2.4 | year |  |
| 2.2 | area | LA |
| 2.2 | title | Intelligence & affect as predictors of Academic Performance among UG students |
| 3.1 | link1 |  |

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

|  |  |  |
| --- | --- | --- |
| **ser** | **subject** | **description** |
| 1.1 | serial | 51 |
| 2.4 | year |  |
| 2.2 | area | LA |
| 2.2 | title | LA in a smart classroom to improve eEducation |

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

|  |  |  |
| --- | --- | --- |
| **ser** | **subject** | **description** |
| 1.1 | serial | 52 |
| 2.4 | year |  |
| 2.2 | area | LA |
| 2.2 | title | Machine Learning Based Student Grade Prediction : Case Study |

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

|  |  |  |
| --- | --- | --- |
| **ser** | **subject** | **description** |
| 1.1 | serial | 53 |
| 2.4 | year |  |
| 2.2 | area | LA |
| 2.2 | title | ML application in MOOCs : Dropout prediction |
| 3.1 | link1 |  |

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

|  |  |  |
| --- | --- | --- |
| **ser** | **subject** | **description** |
| 1.1 | serial | 54 |
| 2.4 | year |  |
| 2.2 | area | LA |
| 2.2 | title | ML approaches to predict learning outcomes in Massive Open Learning Courses |
| 3.1 | link1 |  |

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

|  |  |  |
| --- | --- | --- |
| **ser** | **subject** | **description** |
| 1.1 | serial | 55 |
| 2.4 | year |  |
| 2.2 | area | LA |
| 2.2 | title | Open Student Models of Core Competencies at the Curriculum level : Using LA for Student retention |
| 3.1 | link1 |  |

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

|  |  |  |
| --- | --- | --- |
| **ser** | **subject** | **description** |
| 1.1 | serial | 56 |
| 2.4 | year |  |
| 2.2 | area | LA |
| 2.2 | title | Personalised Multi-Regression Models for Predicting students performance in Course Activities |
| 3.1 | link1 |  |

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

|  |  |  |
| --- | --- | --- |
| **ser** | **subject** | **description** |
| 1.1 | serial | 57 |
| 2.4 | year |  |
| 2.2 | area | LA |
| 2.2 | title | Predicting STEMP achievement with LMS data : Prediction modeling and a Test of an Early Warning System |

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

|  |  |  |
| --- | --- | --- |
| **ser** | **subject** | **description** |
| 1.1 | serial | 58 |
| 2.4 | year |  |
| 2.2 | area | LA |
| 2.2 | title | Predicting Students Performance using Advance Learning Analytics |
| 3.1 | link1 |  |

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

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| --- | --- | --- |
| **ser** | **subject** | **description** |
| 1.1 | serial | 59 |
| 2.4 | year |  |
| 2.2 | area | LA |
| 2.2 | title | When LA meets E-Learning |
| 3.1 | link1 |  |

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

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| **ser** | **subject** | **description** |
| 1.1 | serial | 60 |
| 2.4 | year |  |
| 2.2 | area | LA |
| 2.2 | title | What is LA about ? A Survey of Different Methods used in 2013-15 |
| 3.1 | link1 |  |

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

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| **ser** | **subject** | **description** |
| 1.1 | serial | 61 |
| 2.4 | year |  |
| 2.2 | area | LA |
| 2.2 | title | Potential of LA & Big Data |

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

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| ser | **subject** | description |
| 1.1 | **serial** | 62 |
| 2.2 | **title** | Educational Data Mining: An Application of Data Mining To Estimate Students’ Performance |
| 2.3 | **area** | LA |
| 2.4 | **authors** | Rima Anantkumar Patel, Bhavika Patel, Dweepna Garg, Binal Kaka |
| 2.4 | **year** | 2020 |
| 2.5 | **publication** | Aut Aut Research Journal |
| 5.7 | **results** |  |
| 5.8 | **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 |
| 6.1 | **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 |
| 6.2 | **gaps** |  |
| 4.3 | **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 |
| 4.3 | **chapters** | INTRODUCTION, RELATED WORK, CURRENT ISSUES FACED IN DATA MINING, METHODS OF EDUCATIONAL DATA MINING, APPLICATION OF DATA MINING, RESULT ANALYSIS |
| 1.3 | **dateR** | 22-Apr-2020 |
| 1.2 | **dateA** | 22-Apr-2020 |
| 3.1 | **links** | <http://autrj.com/gallery/13-aut-april-4071.pdf> |

[1] "1.1 serial" "1.2 dateA" "1.3 dateR" "1.4 rating" "2.2 title"

[6] "2.3 area" "2.4 authors" "2.4 year" "2.5 publication" "2.6 type"

[11] "3.1 link1" "3.2 link2" "3.3 citEEE" "3.4 citAPA" "4.1 keywords"

[16] "4.2 abstract" "4.3 chapters" "4.3 tags" "5.1 RQ" "5.2 RO"

[21] "5.4 data" "5.5. factors" "5.6 methods" "5.7 results" "5.8 conclusion"

[26] "6.1 futurework" "6.2 gaps" "6.3 comments" "6.4 myres" "6.5 guide", 5.3 points

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

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| ser | subject | description |
| 1.1 | 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 |

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

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| --- | --- | --- |
| **ser** | **subject** | **description** |
| 1.1 | serial | 64 |
| 2.4 | year | 2013 |
| 2.2 | area | LA |
| 2.2 | 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. |
|  |  | 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 |
|  | citOthers | Using learning analytics to identify successful learners in a blended learning course. Available from: https://www.researchgate.net/publication/259041885\_Using\_learning\_analytics\_to\_identify\_successful\_learners\_in\_a\_blended\_learning\_course [accessed Apr 22 2020]. |
|  | 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.  (4) (PDF) Using learning analytics to identify successful learners in a blended learning course. Available from: https://www.researchgate.net/publication/259041885\_Using\_learning\_analytics\_to\_identify\_successful\_learners\_in\_a\_blended\_learning\_course [accessed Apr 22 2020]. |