



Volume 20, 2021

A LEARNING FUZZY COGNITIVE MAP (LFCM) APPROACH TO PREDICT STUDENT PERFORMANCE

Taha Mansouri	University of Salford, Salford, UK	T.Mansouri@salford.ac.uk
Ahad ZareRavasan*	Masaryk University, Brno, Czech Republic	Ahad.ZareRavasan@econ.muni.cz
Amir Ashrafi	University of Manchester, Manchester, UK	Amir.Ashrafi@postgrad.manchester.ac.uk

* Corresponding author

ABSTRACT

Aim/Purpose	This research aims to present a brand-new approach for student performance prediction using the Learning Fuzzy Cognitive Map (LFCM) approach.
Background	Predicting student academic performance has long been an important research topic in many academic disciplines. Different mathematical models have been employed to predict student performance. Although the available sets of common prediction approaches, such as Artificial Neural Networks (ANN) and regression, work well with large datasets, they face challenges dealing with small sample sizes, limiting their practical applications in real practices.
Methodology	Six distinct categories of performance antecedents are adopted here as course characteristics, LMS characteristics, student characteristics, student engagement, student support, and institutional factors, along with measurement items within each category. Furthermore, we assessed the student's overall performance using three items of student satisfaction score, knowledge construction level, and student GPA. We have collected longitudinal data from 30 postgraduates in four subsequent semesters and analyzed data using the Learning Fuzzy Cognitive Map (LFCM) technique.
Contribution	This research proposes a brand new approach, Learning Fuzzy Cognitive Map (LFCM), to predict student performance. Using this approach, we identified the most influential determinants of student performance, such as student engagement. Besides, this research depicts a model of interrelations among the student performance determinants.

Accepting Editor Man Fung (Kelvin) LO | Received: December 15, 2020 | Revised: April 5, April 20, April 27, 2021 | Accepted: May 1, 2021.

Cite as: Mansouri, T., ZareRavasan, A., & Ashrafi, A. (2021). A learning fuzzy cognitive map (LFCM) approach to predict student performance. *Journal of Information Technology Education: Research*, 20, 221-243.
<https://doi.org/10.28945/4760>

(CC BY-NC 4.0) This article is licensed to you under a [Creative Commons Attribution-NonCommercial 4.0 International License](https://creativecommons.org/licenses/by-nc/4.0/). When you copy and redistribute this paper in full or in part, you need to provide proper attribution to it to ensure that others can later locate this work (and to ensure that others do not accuse you of plagiarism). You may (and we encourage you to) adapt, remix, transform, and build upon the material for any non-commercial purposes. This license does not permit you to use this material for commercial purposes.

Findings	The results suggest that the model reasonably predicts the incoming sequence when there is a limited sample size. The results also reveal that students' total online time and the regularity of learning interval in LMS have the largest effect on overall performance. The student engagement category also has the highest direct effect on student's overall performance.
Recommendations for Practitioners	Academic institutions can use the results and approach developed in this paper to identify students' performance antecedents, predict the performance, and establish action plans to resolve the shortcomings in the long term. Instructors can adjust their learning methods based on the feedback from students in the short run on the operational level.
Recommendations for Researchers	Researchers can use the proposed approach in this research to deal with the problems in other domains, such as using LMS for organizational/institutional education. Besides, they can focus on specific dimensions of the proposed model, such as exploring ways to boost student engagement in the learning process.
Impact on Society	Our results revealed that students are at the center of the learning process. The degree to which they are dedicated to learning is the most crucial determinant of the learning outcome. Therefore, learners should consider this finding in order the gain value from the learning process.
Future Research	As a potential for future works, the proposed approach could be used in other contexts to test its applicability. Future studies could also improve the performance level of the proposed LFMC model by tuning the model's elements.
Keywords	e-learning, Learning Analytics (LA), Learning Fuzzy Cognitive Map (LFCM), Learning Management System (LMS), Student Engagement, Student Performance

INTRODUCTION

The ever-increasing use of data and technology in the education environment has opened new research areas, including Educational Data Mining (EDM), Artificial Intelligence (AI), and Learning Analytics (LA) to effectively manage and use data throughout learning processes (Knight et al., 2020). E-learning refers to IT-based learning and has had a significant impact on educational institutions' quality of learning outcomes (ZareRavasan & Ashrafi, 2019). Numerous institutions are now adopting different forms of e-learning to achieve their learning objectives (Sharma et al., 2017; ZareRavasan et al., 2018). A study by Open University found that producing and providing e-learning courses consumes 90% less energy and has 85% fewer CO₂ emissions per person than face-to-face training (Roy et al., 2004). The global eLearning market is expected to reach a total market value of \$107 billion in 2015 to \$325 billion by 2025, showing that it will have nearly tripled in a decade (Pappas, 2019). As a result, a huge amount of data related to educational processes are generated in every institution. Such data contain useful information that may be analyzed, simulated, and used in decision-making systems. Thus, a new research stream within the data analytics domain emerged called Learning Analysis (LA) (Papamitsiou & Economides, 2014). LA is the calculation, conservation, analysis, and reporting of learning subjects and their context to understand and optimize the very essence of learning and the conditions in which it occurs (Lang et al., 2017). In particular, LA is applying statistical analysis methods over the collected data to get useful insights.

One of LA's main applications is predicting a student (learner) performance or success (Mwalumbwe & Mtebe, 2017; Salinas et al., 2019). Predicting student academic performance is vital because the instructor can take proactive measures (such as one-on-one tutoring and provide remedial lessons) to

improve student learning, especially for low-performed students (Huang & Fang, 2013). The prediction results might help students better understand how they would perform, pushing them to adjust their learning style. For prediction purposes, sophisticated mathematical techniques such as Artificial Neural Networks (ANN), decision trees, and regression are generally applied to a large dataset containing information about previous students on the course. This information could include: (a) things that are known at the start of the course (e.g., the students' previous educational experience and demographic data such as age or gender); (b) things that become known during the course (e.g., login frequency, and post views); and (c) assessment data (e.g., final exam, and quizzes) (Clow, 2013). A model can be developed using this data and then applied to the information available for potential current students to predict how any specific student will perform for the course.

Indeed, prediction models are doing almost the same function as a traditional teacher, observing which students face difficulties in the class and giving them extra support, but in a different e-learning context. However, there are some practical variances. First, the prediction output is a sort of quantitative probabilities rather than the subjective and qualitative understanding of a teacher. Second, the quantitative output could be made available to all relevant stakeholders, not just the teacher. Third, supported with some intelligent agents, the output can be used to trigger proactive supporting actions even without engaging a teacher or a teaching assistant at all (Clow, 2013).

However, the available sets of common prediction approaches, such as ANN and regression, work well with large datasets, face challenges dealing with small sample sizes, limiting their practical applications in real practices (Yoon et al., 2019). Hence, to address this research and practice concern, this research aims to present a brand new approach for student performance prediction using the Learning Fuzzy Cognitive Map (LFCM) approach. FCM is a nonlinear model because a nonlinear transformation function (usually the sigmoid function) transforms the cumulative impact of causal concepts on the effect concept. Therefore, it can capture most of the nonlinearity in complex systems (Salmeron et al., 2019). An advantage of the FCM model over ANN is that FCMs can be interpreted easily by humans, and each FCM node and arc has a specific meaning known to the expert (Salmeron & Froelich, 2016). FCMs can be built over either experts' knowledge extraction or a learning process. In this work, since we had several sequential data, we chose the Learning FCM (LFCM) proposed in Salmeron et al. (2019).

To build our LFCM model, we use a longitudinal quantitative and qualitative dataset of 30 masters students in an online program for three consecutive semesters, trying to predict every individual student's performance for the fourth semester. Employing the LFCM approach, we also map the causal map of effects among observed variables and their impact on student performance.

The rest of the paper is organized as follows. We first present a literature review of the learning analytics and student performance prediction and then FCM applications in an e-learning context. The next section presents the methodology. Next, the results are presented and, finally, we present a discussion and conclude the paper.

LITERATURE REVIEW

LEARNING ANALYTICS AND STUDENT PERFORMANCE PREDICTION

Learning analytics (LA) is defined as “the measurement, collection, analysis, and reporting of data about learners and their contexts, for understanding and optimizing learning and the environments in which it occurs” (Siemens & Long, 2011, p. 34). Regarding the literature, LA is overlapped to some degree with academic analytics and EDM. Academic analytics means the use of business intelligence in the education context, focusing on the institutional and national level, rather than on individual students and courses (Siemens & Long, 2011). The EDM seeks to develop methods for analyzing educational data focusing on the technical challenges rather than on the pedagogical aspects. According to Clow (2013), LA is the first and foremost concern in learning. This can be applied for different

purposes such as student behavior modeling, prediction of performance, prediction of dropout and retention, and resources recommendation (Papamitsiou & Economides, 2014). The task of predicting student performance involves approximating students' future status given a record of the past sequence of behaviors exhibited or activities engaged by a student (Raga & Raga, 2019). A brief overview of the main related previous research on student performance prediction is presented in the following.

One of the main research streams predicts student performance (and clustering them in some cases) based on different quantitative and qualitative data sets. Castellano and Martínez (2008) use collaborative filtering techniques to exploit students' grades to generate group profiles that could facilitate academic orientation. Kumar and Uma (2009) use the classification process to examine various attributes affecting student performance. Lykourantzou et al. (2009) develop multiple feed-forward ANN to predict students' final achievement dynamically and to cluster them in two virtual groups, according to their performance. Moridis and Economides (2009) demonstrate how various pieces of evidence could be combined to optimize inferences about affective states during an online self-assessment test. A method has been developed to predict students' mood and was tested using data emanated from experiments made with 153 high school students. Thai-Nghe et al. (2009) propose improving student performance prediction by dealing with the class imbalance problem, using support vector machines. Yu et al. (2010) use linear support vector machines together with feature engineering and ensembling techniques for predicting student performance. These methods work well in case we have enough meta-data about students and tasks. Abdous et al. (2012) used ordinal logistic regression analysis to predict relationships between online question theme and final grade. Pardos et al. (2013) build a unified model that predicts student standardized examination scores from a combination of student effect, disengaged behavior, and performance within the learning system. More recently, Meghji et al. (2018), using Association Rule Mining and Pattern Discovery in the context of a higher educational institute, observe that student class performance is directly influenced by the attention given to a lecture, proper note-taking and the tendency to self-solve assignments.

Considering the literature, scholars also tried to develop tools to support learners and facilitate the learning process. For instance, Romero-Zaldivar et al. (2012) develop some virtual appliances to monitor students' behavior and progress and then correlate them to the final grade. In this line, researchers have recently proposed using recommender system techniques (e.g., matrix factorization) to predict student performance (Thai-Nghe et al., 2012; Toscher & Jahrer, 2010). Extended from these works, Thai-Nghe et al. (2011) propose tensor factorization models to consider the sequential effect (for modeling how student knowledge changes over time). Moreover, Thai-Nghe et al. (2012) extend their work by introducing a new method of "tensor factorization forecasting" for predicting student performance. Macfadyen and Dawson (2010) analyze the Learning Management System (LMS) tracking data from a course that identified 15 variables demonstrating a significant correlation with students' final grades. They also develop an early warning system for educators. Along the same lines, Vialardi et al. (2011) used data mining techniques that employed the students' academic performance records to design a recommender system in support of the enrolment process. Raga and Raga (2019) develop a prediction model for student performance in the early stages of blended learning courses using deep neural network architecture and utilizing online activity attributes as input patterns.

Researchers recently focused mainly on a comparative analysis of the accuracy of different machine learning methods in student performance prediction applications. For instance, Huang and Fang (2013) develop and compare four types of mathematical models (i.e., multiple linear regression model, the multilayer perception network model, the radial basis function network model, and the support vector machine model) to predict student academic performance. Abdulwahhab and Abdulwahab (2017) also used the Prediction Tree (CPT+) algorithm to predict the next grade for upcoming courses or the registered course(s) and find that it outperforms other prediction models. Umer et al. (2018) conduct a comparative analysis of four predictive models; Random Forest, Naive Bayes, K-Nearest Neighbor, and Linear discriminant analysis, to predict student performances. Al Breiki et al.

(2019) compared the accuracy of different machine learning methods (i.e., SMOReg, Random Forest, Linear Regression, Multilayer Perceptron, K-Nearest Neighbor, Gaussian, Processes Random Tree, Decision Table, and Simple Log Regres) in predicting student performance at the United Arab Emirates University (UAEU). Sheshadri et al. (2018) use Logistic Regression, Decision Tree, and K-Nearest Neighbor classifiers to predict student performance using data generated before the test and over the course during the semester. Using the model, they classify students into distinction/non-distinction groups. Turabieh (2019) applies a hybrid feature selection algorithm with different machine learning classifiers (i.e., K-Nearest Neighbor, Convolutional Neural Network (CNN), Naive Bayes, and Decision Tree) to predict the student's performance. They also apply a binary genetic algorithm as a wrapper feature selection. In addition, Mohammadi et al. (2019) apply three supervised learning algorithms (K-Nearest Neighbor, Naive Bayes, and Decision Tree) for student performance prediction. Masood et al. (2019) implemented 11 machine learning models to predict student performance using two public student databases. According to the results, Decision Tree and Random Forest are the machine learning models with the highest accuracy.

This short review shows that prior research applied different variables and techniques to model and predict student learning performance. Linear models such as linear and logistic regression were the mainstream applications in early research because of their simplicity and ability to account for certain linear patterns between available input variables and student achievement. More advanced methods, such as ANN, CNN, Naive Bayes, and Decision Tree, have been applied later. Due to different levels of complexity of these methods, recent studies attempted to compare different models' accuracy in predicting student performance. However, as most of the adopted models contain many parameters to adjust and they pass data through a number of transforming layers, they only work well with large datasets and have serious shortcomings with small sample sizes (Yoon et al., 2019).

FCM IN THE E-LEARNING CONTEXT

Nowadays, FCMs play an important role in different scientific fields, including e-learning and the LMS context. FCM has been applied in this field to address different research aims. For instance, some research adapted FCM to model interrelations among factors affecting LMS or learning. In this line, Salmeron (2009) employs an Augmented FCM for modeling Critical Success Factors (CSFs) in LMS. Nownaisin et al. (2012) identify the causalities of the education management of the Thailand science-based technology school. Yesil et al. (2013) model the control engineering educational CSFs. Takacs et al. (2014) introduce a novel FCM algorithm to calculate the values of the interrelation levels between the factors in a system for the students' grade evaluation.

Others used FCM to model the design, adoption, or assessment of LMS. For instance, Tsadiras and Stamatis (2008) examine the use of FCMs for planning network learning and enhancing the success of learning programs. Hossain and Brooks (2008) model educational software adoption at three UK secondary schools based on stakeholders' perceptions. Georgiou and Botsios (2008) identify learning styles in adaptive educational hypermedia systems. Baron et al. (2015) present a learning assessment system that uses multivariate analysis based on Structural Equation Modeling (SEM), facilitating the assessment of learning in interactive environments.

Some others incorporated FCM in the tasks and process of learning and learning tools. For instance, Van Vliet et al. (2010) describe an updated framework for the participatory scenario, bridging the gap between storylines and models. Yang et al. (2011) propose a set of student progress indicators based on FCM to comprehensively describe student progress on various aspects together with their causal relationships. Chrysafiadi and Virvou (2013) propose an FCM based knowledge representation approach to support navigation in an adaptive learning system. Chrysafiadi and Virvou (2014) use FCM for Adaptive Instruction in an e-learning environment for computer programming. Peña et al. (2007) model the teaching-learning environment and simulate the bias exerted by authored lectures on students' learning. Anusha and Ramana (2015) analyze the symptoms of stress on college students using the combined disjoint block FCM model. Dias et al. (2015) propose an FCM of LMS users' quality

of interaction within higher education blended-learning environments. Fatahi and Moradi (2016) propose an FCM model to calculate a user’s desirability based on personality in e-learning environments. Sweta and Lal (2016) develop a learner model for automatic detection of learning style using FCM in an adaptive e-learning system. Kireev (2016) develop an FCM model for optimizing e-learning courses. Sweta and Lal (2016) propose a personalized adaptive learner model in e-learning system using FCM and Fuzzy Inference System.

Other research streams in the application of FCM in the learning discipline applied FCM in the decision-making process. For instance, Georgopoulos et al. (2014) expand the utilization of FCM based on medical decision support systems for learning and educational purposes using a scenario-based learning approach. Baykasoğlu and Gölcük (2015) propose a new model that integrates Fuzzy TOPSIS and FCMs to model and solve decision problems related to industrial engineering. Pandey and Singh (2015) propose an FCM based recommender system for e-learning system with a multi-agent framework. Aguilar (2016) proposes a recommender learning resource in a smart classroom using FCM.

This review shows that FCM has the potential to address different research and practice problems in the learning discipline. Despite this, no attempt has been made to leverage the FCM’s potentials to predict student performance.

RESEARCH METHOD

The purpose of this study is to present a model to predict student performance using the LFCM approach. To achieve this goal, we utilized a research structure based on a literature review to identify factors as antecedents of student performance, longitudinal data, and LFCM as the data analysis procedure. The main research steps are illustrated in Figure 1.

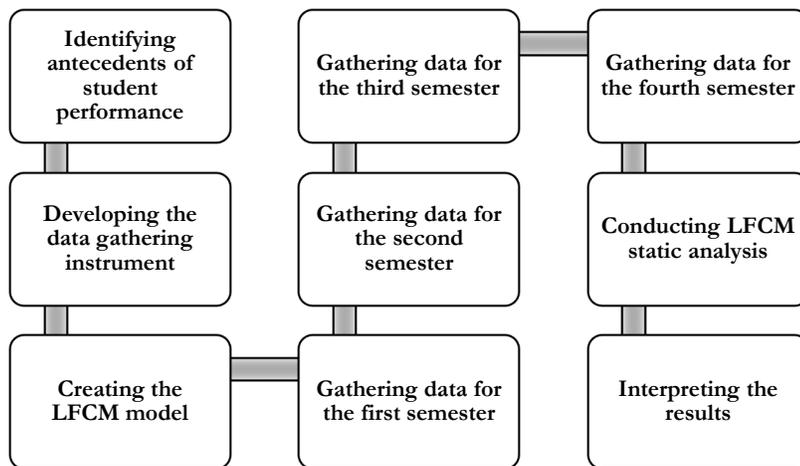


Figure 1. The research steps

LEARNING FCM

FCMs are a combination of ANNs and Fuzzy Logic. They are fuzzy weighted digraphs, including several nodes and arcs (Salmeron & Froelich, 2016). FCMs define relationships using fuzzy terms such as very low or high while describing complex systems, including interrelated concepts (Salmeron et al., 2019). The nodes or concepts (C_i) and related weighted arcs (W_{ij}) display the modeled problem and causal dependencies between them, respectively (Salmeron & Froelich, 2016). Therefore, each W_{ij} sign shows the direction of causality between concepts C_i and C_j , whereas its amount shows the intensity of that effect. The values of concepts are in the range of $[0,+1]$, and the weights are in the

range of $[-1,+1]$. Moreover, a combination of concepts summarizes a snapshot of the modeled system at any time, as a state vector $A = \{A_1, \dots, A_N\}$, in which N is the number of concepts, and A_i is the value of C_i . In order to update A_i at each time, the following rule is proposed (Salmeron et al., 2019):

$$A_i^t = f(A_i^{t-1} + \sum_{j \neq i, j=1}^N A_j^{t-1} W_{ji}) \quad \text{Eq(1)}$$

where A^t is the value of concept C_i at time t , A^{t-1} the value of concept C_i at time $t - 1$, and W_{ji} the connection from C_j to C_i . The function f is an activation function to map and bound the result in an interval; and for this work, we use the unipolar sigmoid as proposed in (Bueno & Salmeron, 2009) as follows:

$$f(x) = \frac{1}{1+e^{-ax}} \quad \text{Eq(2)}$$

where x is described as the value of A_i and a is a real positive number modeling the function's slope.

There are two types of analyses in FCMs as static and dynamic. Static analysis displays the concepts' causal effects using the maximum amount among different paths from input concepts ending to target concepts (ZareRavasan & Mansouri, 2014). In this analysis, at first, a casual path from a concept node C_i to another concept node C_j , through other nodes, say $C_i \sim C_{k1}, C_{k1} \sim \dots C_{kn}, C_{kn} \sim C_j$ can be indicated by sequence $(i, k1, \dots, kn, j)$. Then the indirect effect of C_i on C_j is the causality $C \sim I$ impart to C_j via the path $(i, k1, \dots, kn, j)$. The total effect of C_i on C_j is the composite of all indirect effect causalities $C \sim$ imparts to C_j .

A simple fuzzy causal algebra is created by interpreting the indirect effect of the operator I as the minimum operator (or t-norm) and the total effect of operator T as the maximum operator (or s-norm) on the partially ordered set P of causal values (so we simply call it as the maximum of minimums). Formally let \sim be a causal concept space and let $e: \sim \times \sim \rightarrow P$ be a fuzzy causal edge function, and assume that there are m -many causal paths from C_i to C_j ; $(i, k^1 \dots k^r, j)$ for $1 \leq r \leq m$. Then let $Ir(C_i, C_j)$ denote the indirect effect of concept C_i on concept C_j via the " r "th causal path, and let $T(i, C_j)$ denote the total effect of C_i on C_j over all m causal paths. These operators are shown in Eq(3) and Eq(4):

$$I \sim (C_i, C_j) = \min(w(C_p, C_{p+1}): (p, p+1) \sim (i, k^1 \dots k^r, j)) \quad \text{Eq(3)}$$

$$T(C_i, C_j) = \max(Ir(C_i, C_j)), \text{ where } 1 \leq r \leq m \quad \text{Eq(4)}$$

where p and $p+1$ are contiguous left to right path indices (Kosko, 1986).

The dynamic analysis starts with an initial state vector such as $A = \{A_1, \dots, A_N\}$; and keep updating with Eq (1) and Eq (2) until reaching an equilibrium point in which the amounts of the resulted vector have plateau (Hobbs et al., 2002).

FCMs can be constructed either by experts or historical data. However, there are some limitations in relying on experts' subjective opinions (Kahvandi et al., 2018; ZareRavasan & Mansouri, 2016). The learning approaches for FCMs are concentrated on learning the weighted matrix W , based either on expert intervention or available historical data (Papageorgioua & Kannappan, 2012). There are various learning approaches to train the FCM's weight matrix, mostly from the ANN discipline (Salmeron et al., 2019). In this paper, we use Modified Asexual Reproduction Optimization (MARO) proposed by Salmeron et al. (2019).

The main objective function of FCM-MARO is minimizing the following error:

$$\text{in-sample-error} = \frac{1}{(K-1)N} \sum_{t=1}^K \sum_{n=1}^N |C_n(t) - \hat{C}_n(t)| \quad \text{Eq(5)}$$

where $C_n(t)$ is the original value of the concept n at time t , $\hat{C}_n(t)$ is the calculated value of that concept using the candidate FCM and Eq (1) and Eq (2), K is the number of input observations and N is

the number of concepts. The following is the pseudocode of FCM-MARO algorithm (Salmeron et al., 2019).

```

t = 1 // Initial time setting
loc = 1 //Initial local number setting
P = initialize(L,U) // Creating a randomly generated weight matrix as parent, bounded between
    lower and upper thresholds
errorP = Cost(P) // Calculated regarding Eq(5)
While stopping_conditions ≠ true do
    bud_t = reproduce(P) // Generating a randomly modified offspring from the parent (P)
    error_bud_t = Cost (bud_t)
    if error_bud_t < errorP then P= bud_t, loc =1;
    else if error_bud_t + Δt > errorP then P= bud_t;
    else clear(bud_t), loc ++
    
```

Where t is time, loc shows the number of times in which the algorithm has no improvement, P is a randomly generated weight matrix as a parent, and the cost function is simply calling Eq (5). This algorithm starts with generating a random offspring from the pattern using a strategy namely budding (fully explained in Mansouri et al. [2011] and Farasat et al. [2010]) and calling the cost function for this generated offspring. If the error of the new solution is less than its parent, we accept it, remove the parent and make it as a new parent. However, we will accept the generated solution if its error is not greater than Δ_t amount from its parent error. Δ_t Is calculated using Eq (6). Finally, we discard the offspring if it meets none of these conditions.

$$\Delta_t = \frac{\ln(loc)}{\sqrt{t}} \tag{Eq(6)}$$

The algorithm ends when it gets to the stopping condition. The final solution is the aimed FCM’s weight matrix.

DEVELOPING THE DATA GATHERING INSTRUMENT

A review of the recent relevant literature has been conducted to prepare the research data gathering instrument. Six distinct categories of antecedents are identified as course characteristics (six items), LMS characteristics (four items), student characteristics (five items), student engagement (12 items), student support (seven items), and institutional factors (three items), along with measurement items within each category. Furthermore, we assessed the student’s overall performance using three items of OP1: student satisfaction score, OP2: knowledge construction level, and OP3: student GPA (Grade Point Average). Excluding measurement items under the student engagement category (SE1 to SE12, or part B of the questionnaire) extracted directly from the Moodle LMS, others (Part A) were surveyed through online questionnaires (see Appendix A for the list of measured items).

CREATING THE LFCM MODEL

To create the LFCM model, we used the 37 antecedents as the model’s first layer and three performance indicators as the second layer (see Figure 2 as a simplified representation of the developed LFCM model). Longitudinal data from three consecutive semesters has been exploited to model the interdependencies.

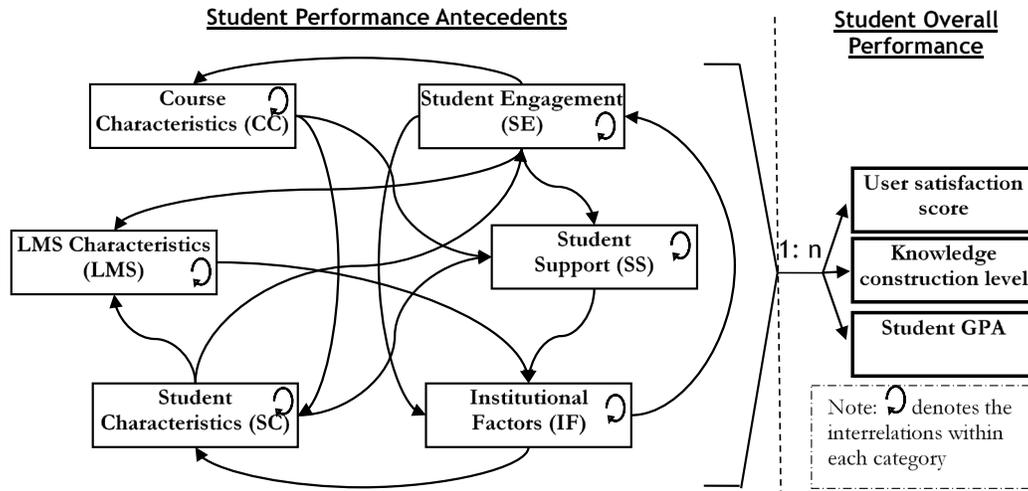


Figure 2. Partial and high-level cognitive map of student overall performance and antecedents

DATA GATHERING PROCEDURE

A longitudinal set of data has been gathered and used to run the research model. The same set of 45 students in an Information System masters program (only course-based enrollments) at an online university (during a four-semester period) has been targeted as the research sample. This university uses Moodle LMS, which is an open-source e-learning platform. A questionnaire (for Part A) has been developed and distributed using the “questionnaire” plugin of Moodle, capable of linking and tracing responses back to students.

At the end of each semester, the sample students were asked to fill the questionnaire’s Part A. Data for part B (i.e., SE1 to SE12) has been extracted from the Moodle LMS. To date, to the best of the authors’ knowledge, there are no publicly available codes/reports at Moodle to extract this data set. Therefore, SQL queries have been developed and ran to secure access to the required fields. Besides, as most of the measurement items were sums or averages across different courses’ data, we ran such calculations on separate spreadsheets. For the fourth semester, the students were asked only to answer OP1, OP2, and OP3. Data for the fourth semester will be used to evaluate the accuracy of the fourth semester’s predicted performance scores. At the end of the period, we had 30 (out of 45) valid sample data, as some responses to questionnaire items were not valid, and some of the students quit their program. The data-gathering period was: (1) autumn 2018, (2) spring 2018, (3) autumn 2019, and (4) spring 2019. The individual student performance is predicted for the fourth period, i.e., spring 2019, and compared with the same period’s actual student performance data. For the sake of privacy and ethical issues, data has been anonymized before the analysis.

FINDINGS

PREDICTING STUDENT PERFORMANCE

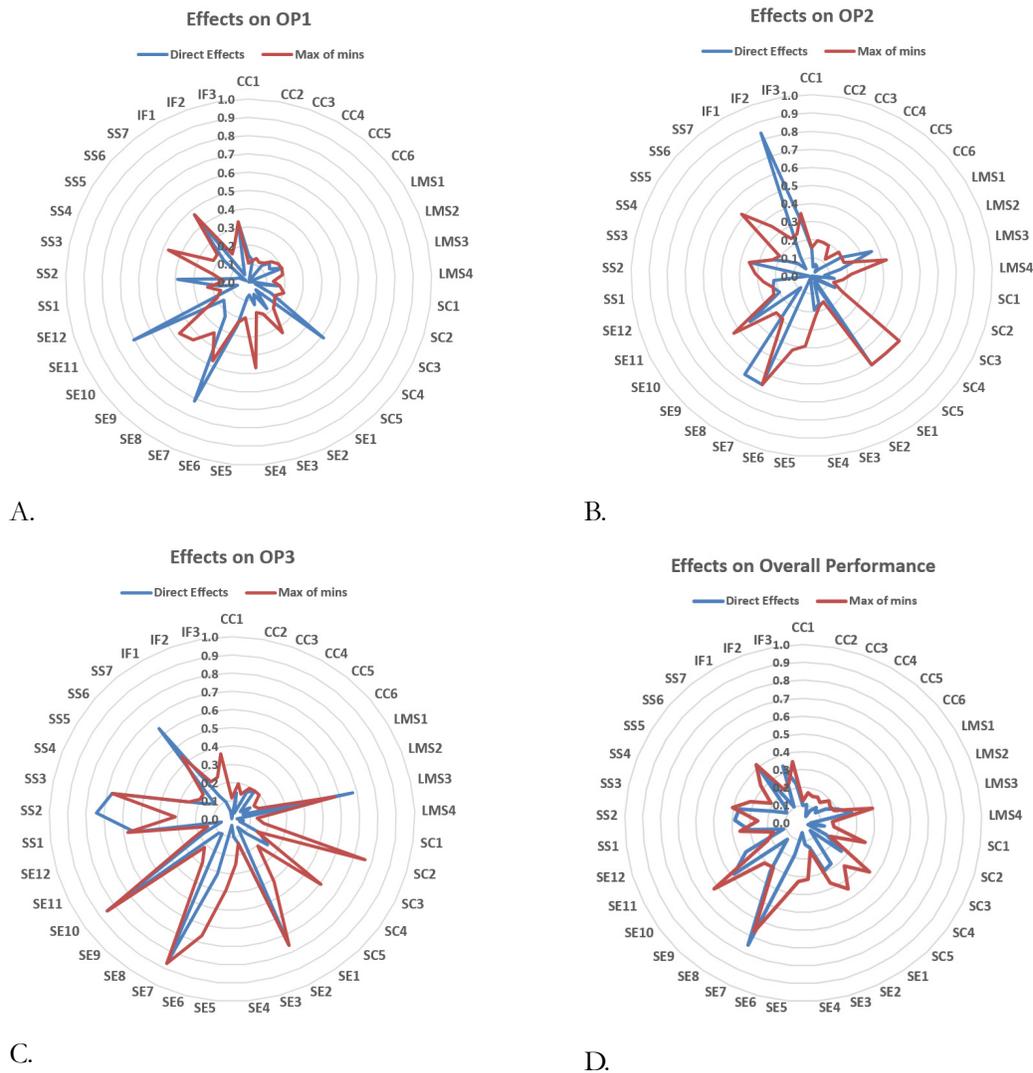
In this section, we considered each student separately to construct his/her own FCM regarding performance antecedents (A_i) and overall performance (P_i) for three semesters, using the algorithm described in the Learning FCM section above. We applied the resulted FCM as a special type of Recurrent Neural Network for predicting the overall performance in the last (fourth) semester for each student case. MSE and Standard deviation for three performance indicators (OP1, OP2, and OP3) are presented in Table 1. These values display a good performance of the predicting model, having in mind the small sample size.

Table 1. MSE and Standard deviation for performance variables

Measure	OP1	OP2	OP3
MSE	0.07783908	0.07463091	0.05041522
StDev	0.05817604	0.08766665	0.05861402

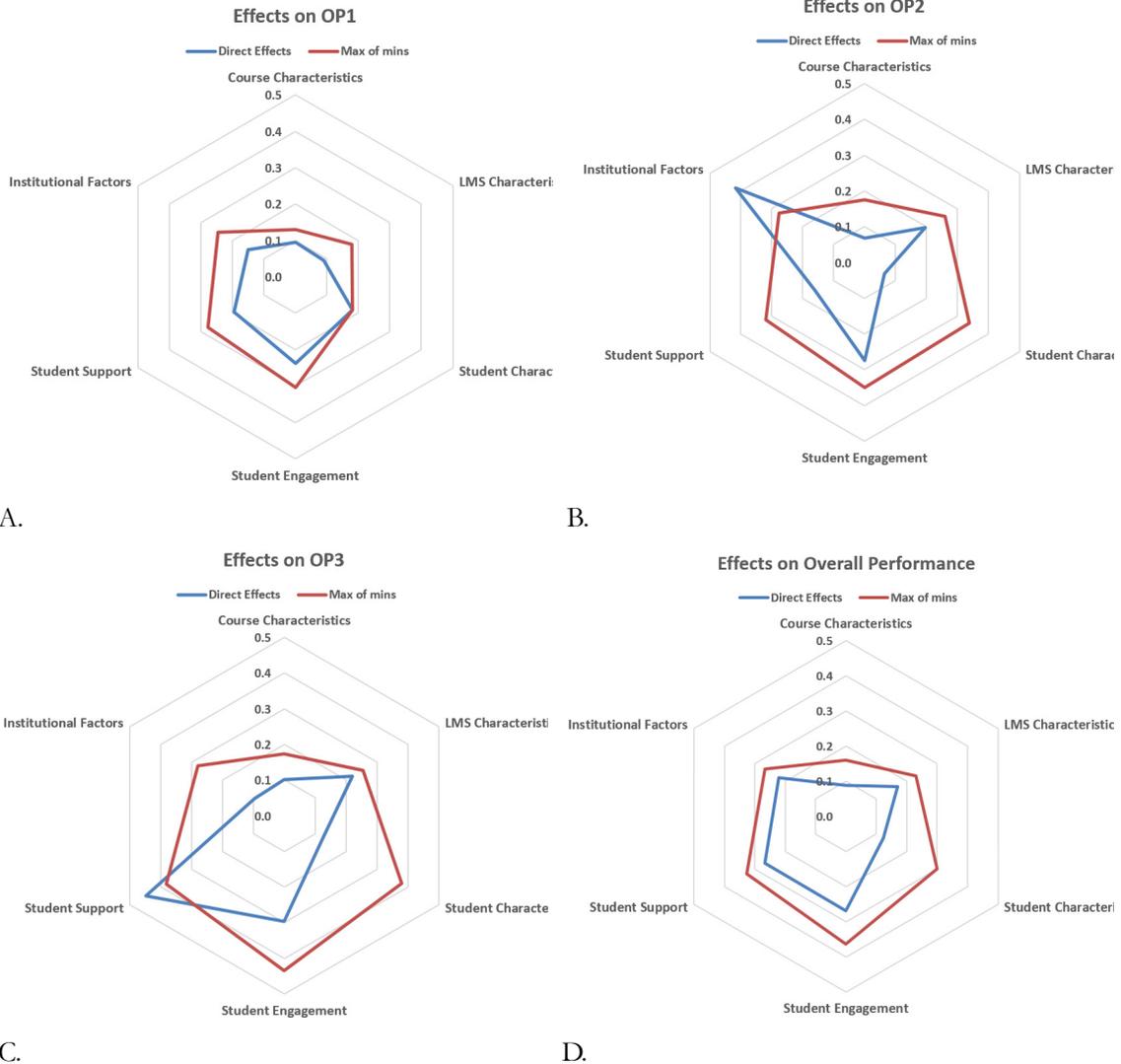
THE EFFECTS OF ANTECEDENTS ON STUDENT PERFORMANCE

Based on the augmented adjacency matrix among student performance antecedents (A_i), and student's overall performance (P_i), and equations 1-4, the path effect from student performance antecedents to student overall performance ($A_i \sim P_j$) can be calculated. The results of the calculations are presented in Figures 3 and 4.



Note: To plot part D, means of OP1, OP2, and OP3 are used.

Figure 3. The direct and indirect effects of student performance antecedents on performance



A.

B.

C.

D.

Note: To plot part D, means of OP1, OP2, and OP3 are used.

Figure 4. The direct and indirect effects of categories of student performance antecedents on performance

It is observable from the values in Figures 3 and 4 that the indirect (maximum of minimums drawn by Eq (3) and Eq (4), shown in red line) effects for almost all variables are larger than the associated values for direct effects (blue lines). It should be noted again that the maximum of minimum operator traverses all connecting paths between two concepts, assign the minimum graph value to each path and select that path containing the highest value. Through this approach, the operator can capture indirect effects between two concepts.

For instance, according to Figure 3, part A, S11 has a very strong direct effect on OP1. However, when we count the network of interrelations among all factors, its indirect effect is minor. On the other hand, according to Figure 3, part B, SC4 depicts a minor direct effect while a strong indirect effect on OP2. Such results depict that the causal relations and indirect effects are important and can be intensified or diminished through interrelationships among the proposed model's factors.

Figure 4 illustrates the magnitude of the categories' effects on each performance indicator and overall performance. It can be observed from the figures that student engagement carries the largest effect (see part D), while student characteristics experienced the highest augmentation, as the effect size is scaled up from 0.124 in the direct effect to 0.300 in the max of mins effect.

THE CAUSAL INTERRELATIONS AMONG PERFORMANCE ANTECEDENTS

Figure 5 also illustrates the causal interrelations among student performance antecedents (see Appendix B for further details). The X-axis indicates each variable's causal magnitude (rows in Appendix B). The Y-axis shows the magnitude of effects (columns in Appendix B). Based on this, we classify factors into four clusters. The cluster in quadrant 1 includes "autonomous" factors that have weak cause and weak effect. These factors are relatively disconnected from the system. It means that the level or magnitude of the factors belonging to this cluster has nothing to do with other variables' magnitude. The cluster in quadrant 2 includes "independent" factors with a strong cause but a weak effect. As the title suggests, this cluster's factors act independently, and based on the positive or negative relationship, intensify or weaken the magnitude of other variables. The cluster in quadrant 3 consists of dependent factors that have a weak cause but a strong effect. Finally, quadrant 4 includes "linkage" factors that have strong cause and effect.

Regarding this, CC#; Course Characteristics, and LMS#; LMS Characteristics mainly fall under quadrant 1, indicating that those variables neither causing nor getting affected by other factors. Variables associated with SE#; Student Engagement and SS#; Student Support also mainly fall under quadrant 2, indicating a strong cause on others, with a moderate effect from other variables. Besides, according to quadrant 2, it can be observed that two out of three institutional factors (IF2 and IF3) fall under this category, proposing that the quality of the infrastructure, hardware, and software of the institute are affecting other variables while receiving the least influence from others. It is also apparent from quadrant 1 of the figure that CC#; course characteristics' items fall here. Meanwhile, they have the least impact on others, indicating that an improved level of the underlying variables will not lead to enhanced levels at other variables.

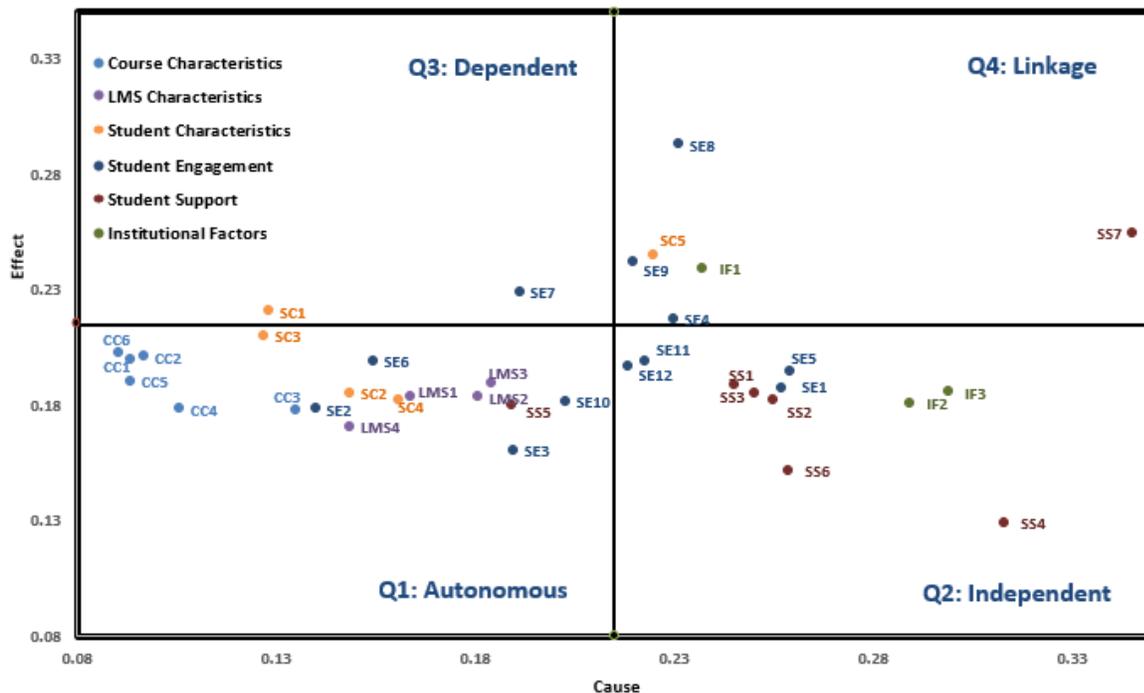


Figure 5. Causal interrelations among student performance antecedents

DISCUSSION

This research aims to propose a brand-new approach for student performance prediction using the LFCM approach. To build our LFCM model, we use a longitudinal quantitative and qualitative dataset of 30 masters students in an online program for three consecutive semesters, trying to predict every individual student's performance for the fourth semester. Employing the LFCM approach, we also map the causal map of effects among the observed factors and their impact on student performance. Below, the results obtained is discussed in detail.

Among all factors we identified in the literature, the results show that SE7: total time online, and SE10: the regularity of learning interval in LMS, have the largest effect on overall performance (see Figure 3, part D). It is not a surprising result, as the more time and effort learners regularly dedicate to learning, the more likely they will construct and develop their body of knowledge and outperform other inactive students. This argument is well in line with the findings of prior research (Siegle et al., 2010).

According to Figure 4, Part D, and Figure 5, our findings showed that the course characteristics (e.g., course plan and learning material) category has the least direct influence on overall performance. This finding is completely different from previous findings (Cheng & Chau, 2016). We also found that this category falls under the autonomous quadrant, meaning that it has the least influence on other factors. In contrast, it has been affected moderately by other factors. Similarly, student characteristics (e.g., attitude, self-efficacy, and experience) has the second least direct influence on overall performance. Items of student characteristics do not depict a significant impact on other variables. We also found that the LMS characteristics category is placed third in terms of the least direct effects on a student's overall performance, with items that fall under the first quadrant. We can conclude that the items belonging to these three categories act autonomously and do not strongly intensify other variables. It does not mean that the related variables are not important in the interrelations among the observed variables. Nevertheless, it argues that the intensity of the relationship is weaker compared to other influencing variables. Therefore, we do not contradict previous research that proposed significant relationships between different elements presented in our model. For instance, previous studies highlighted the role of LMS on the quality of learning. They mentioned that LMS could support ubiquitous learning by giving students access to learning materials anytime, anywhere, and everywhere. It can also help students acquire team-based skills and support collaborative learning, active engagement, and participation in course activities (Nwokeji et al., 2019). However, we argue that in the network of interrelations in our model, the role of other factors outweighs the role of LMS on student performance and on the magnitude of other variables.

Interestingly, the student engagement category has the highest direct effect on a student's overall performance (see Figure 4, Part D). Student engagement primarily focuses on the time and effort put by the students on the educational activities to achieve the desired learning outcomes and is considered as a proxy for learning outcomes (Pye et al., 2015). Therefore, students' learning effectiveness and satisfaction should be improved by designing systems and instilling strategies that facilitate, encourage, and reward their engagement (Hu & Hui, 2012). Moreover, learning engagement, which is an important antecedent for learning outcome, is lower for technology-mediated learning than face-to-face learning (Hu & Hui, 2012). It is a good point because, from a pedagogical perspective, e-learning systems have several difficulties transferring emotion or even engage students during a course session (Muntean, 2011). To do so, LMS has to focus on raising students' engagement in classes to reach a higher level of performance. In this regard, the learning process should encompass more interactive and gamified material to gain greater attention from learners. It also strives to encourage users to engage in desired behaviors in connection with the applications. For instance, we can convert points or badges into *virtual goods* or even get discounts for tuition fees. Students will engage more with the application and be motivated to earn more points to benefit from these advantages (Muntean, 2011).

We observed a strong impact of student support on overall performance according to Figure 4, Part D, and a significant effect on other variables, according to Figure 5. Most items in this category fall under the fourth quadrant, meaning that they mostly act independently. In other words, improving the level of student support will indirectly result in improvements on other items. One of the interesting findings of this study is that SS7: subjective norm has the strongest influence on other factors (see Figure 5). Subjective norm refers to the person's perception that most people who are important to the person think the person should or should not perform the behavior in question (Ashrafi et al., 2020). This clearly shows that students' perception has a great influence on the overall performance and other factors. To be clear, the subjective norm makes users compare their initial expectations with their modified perceptions. The strong impact of student support elements on other variables is not surprising, as a proper support level can positively affect student engagement, attitudes towards using the LMS, and attending actively in the course. This finding is well in line with prior research results (Grant-Vallone et al., 2003; Hughes & Kwok, 2006).

Establishing action plans to boost student performance should focus on the performance antecedents and the interrelations among them. Figure 5 presents valuable insights for decision-makers when limited resources come into the decision-making context, and educational institutes need to choose which educational aspects they should focus. The presented four-dimensional profile in Figure 4 could be constructive here by highlighting the most important categories and individual factors. More specifically, variables in quadrant 2 and 4 of Figure 5 (with the highest cause) should be of more focus while establishing improvement action plans, as any improvements here will also result in an improved level of affected factors, without direct improvement plans over there.

CONCLUSION

This research proposes a new approach for student performance prediction using the LFCM approach. As mentioned before, although the available set of common prediction approaches, such as ANNs or logistic regression, work well with large datasets, they face challenges dealing with small sample sizes, limiting their practical applications in real practices. Given this limitation, it is important to present a new approach for student performance prediction using new approaches such as LFCM. From this perspective, the proposed LFCM model constitutes practical and managerial implications for the e-learning community. We found that the student engagement category has the highest direct effect on a student's overall performance and student support strongly intensifies other items in our proposed model. Even though our study offers some contributions, it suffered from several limitations that must be tackled in future studies. First, this study is by no means comprehensive to address all student performance antecedents. Even though we reviewed the most relevant and recent literature to identify the performance determinants, we were confined with the length of the questionnaire (especially in longitudinal research) and a set of indices we could extract from Moodle. Second, we do not aim to claim our findings' generalizability, as our results are based on a single master's program and a single university. So simply, the interrelationships are extracted and interpreted for a limited context. As a potential for future work, the proposed approach could be used in other contexts to test its applicability. Third, it is important to stress that the predictive power of LFCM models is far from perfect and far from other techniques such as ANN and regression. However, LFCM performs well on limited sample sizes. Future studies could improve the performance level of the proposed LFCM model by tuning the model's elements.

REFERENCES

- Abdous, M., Wu, H., & Yen, C.-J. (2012). Using data mining for predicting relationships between online question theme and final grade. *Journal of Educational Technology & Society*, 15(3), 77.
- Abdulwahhab, R. S., & Abdulwahab, S. S. (2017, December). Integrating learning analytics to predict student performance behavior. *6th International Conference on Information and Communication Technology and Accessibility, Muscat, Oman*. (pp. 1-6). IEEE. <https://doi.org/10.1109/ICTA.2017.8336060>

- Aguilar, J. (2016). Multilayer cognitive maps in the resolution of problems using the FCM designer tool. *Applied Artificial Intelligence*, 30(7), 720-743. <https://doi.org/10.1080/08839514.2016.1214422>
- Al-Azawei, A., Parslow, P., & Lundqvist, K. (2016). Barriers and opportunities of e-learning implementation in Iraq: A case of public universities. *The International Review of Research in Open and Distributed Learning*, 17(5). <https://doi.org/10.19173/irrodl.v17i5.2501>
- Al Breiki, B., Zaki, N., & Mohamed, E. A. (2019, November). Using educational data mining techniques to predict student performance. *International Conference on Electrical and Computing Technologies and Applications, Ras Al Khaimah, United Arab Emirates* (pp. 1-5). <https://doi.org/10.1109/ICECTA48151.2019.8959676>
- Anusha, G., & Ramana, P. V. (2015). *A study on symptoms of stress on college students using combined disjoin tblock fuzzy cognitive maps (CDBFCM)*: Infinite Study.
- Ashrafi, A., ZareRavasan, A., Savoji, S. R., & Amani, M. (2020). Exploring factors influencing students' continuance intention to use the learning management system (LMS): A multi-perspective framework. *Interactive Learning Environments*, 1-23. <https://doi.org/10.1080/10494820.2020.1734028>
- Baloyi, G. P. (2014a). Learner support in open distance and e-learning for adult students using technologies. *Journal of Communication*, 5(2), 127-133.
- Baloyi, G. P. (2014b). Learner support in the open distance learning and e-learning context using the community of inquiry model. *Mediterranean Journal of Social Sciences*, 5(20), 1251-1251. <https://doi.org/10.5901/mjss.2014.v5n20p1251>
- Barón, H. B., Crespo, R. G., Espada, J. P., & Martínez, O. S. (2015). Assessment of learning in environments interactive through fuzzy cognitive maps. *Soft Computing*, 19(4), 1037-1050. <https://doi.org/10.1007/s00500-014-1313-x>
- Baykasoğlu, A., & Gölcük, I. (2015). Development of a novel multiple-attribute decision making model via fuzzy cognitive maps and hierarchical fuzzy TOPSIS. *Information Sciences*, 301, 75-98. <https://doi.org/10.1016/j.ins.2014.12.048>
- Bueno, S., & Salmeron, J. L. (2009). Benchmarking main activation functions in fuzzy cognitive maps. *Expert systems with Applications*, 36(3), 5221-5229. <https://doi.org/10.1016/j.eswa.2008.06.072>
- Castellano, E. J., & Martínez, L. (2008, July). Orieb, a Crs for academic orientation using qualitative assessments. *Proceedings of the LADIS International Conference e-Learning, Amsterdam, The Netherlands*, 38-43.
- Chawinga, W. D., & Zozie, P. A. (2016). Increasing access to higher education through open and distance learning: Empirical findings from Mzuzu University, Malawi. *International Review of Research in Open and Distributed Learning*, 17(4), 1-20. <https://doi.org/10.19173/irrodl.v17i4.2409>
- Cheng, G., & Chau, J. (2016). Exploring the relationships between learning styles, online participation, learning achievement and course satisfaction: An empirical study of a blended learning course. *British Journal of Educational Technology*, 47(2), 257-278. <https://doi.org/10.1111/bjet.12243>
- Chrysafiadi, K., & Virvou, M. (2013). A knowledge representation approach using fuzzy cognitive maps for better navigation support in an adaptive learning system. *SpringerPlus*, 2(1), 81. <https://doi.org/10.1186/2193-1801-2-81>
- Chrysafiadi, K., & Virvou, M. (2014). Fuzzy logic for adaptive instruction in an e-learning environment for computer programming. *IEEE Transactions on Fuzzy Systems*, 23(1), 164-177. <https://doi.org/10.1109/TFUZZ.2014.2310242>
- Clow, D. (2013). An overview of learning analytics. *Teaching in Higher Education*, 18(6), 683-695. <https://doi.org/10.1080/13562517.2013.827653>
- Dias, S. B., Hadjileontiadou, S. J., Hadjileontiadis, L. J., & Diniz, J. A. (2015). Fuzzy cognitive mapping of LMS users' quality of interaction within higher education blended-learning environment. *Expert Systems with Applications*, 42(21), 7399-7423. <https://doi.org/10.1016/j.eswa.2015.05.048>
- Farasat, A., Menhaj, M. B., Mansouri, T., & Moghadam, M. R. S. (2010). ARO: A new model free optimization algorithm inspired from asexual reproduction. *Applied Soft Computing*, 10(4), 1284-1292. <https://doi.org/10.1016/j.asoc.2010.05.011>

- Fatahi, S., & Moradi, H. (2016). A fuzzy cognitive map model to calculate a user's desirability based on personality in e-learning environments. *Computers in Human Behavior*, 63, 272-281. <https://doi.org/10.1016/j.chb.2016.05.041>
- Ferguson, J. M., & DeFelice, A. E. (2010). Length of online course and student satisfaction, perceived learning, and academic performance. *The International Review of Research in Open and Distributed Learning*, 11(2), 73-84. <https://doi.org/10.19173/irrodl.v11i2.772>
- Georgiou, D. A., & Botsios, S. D. (2008). Learning style recognition: A three layers fuzzy cognitive map schema. *Proceedings of the 2008 IEEE International Conference on Fuzzy Systems*, 2202-2207. <https://doi.org/10.1109/FUZZY.2008.4630675>
- Georgopoulos, V. C., Chouliara, S., & Stylios, C. D. (2014). Fuzzy cognitive map scenario-based medical decision support systems for education. *Proceedings of the 36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, 1813-1816. <https://doi.org/10.1109/EMBC.2014.6943961>
- Grant-Vallone, E., Reid, K., Umali, C., & Pohlert, E. (2003). An analysis of the effects of self-esteem, social support, and participation in student support services on students' adjustment and commitment to college. *Journal of College Student Retention: Research, Theory & Practice*, 5(3), 255-274. <https://doi.org/10.2190/C0T7-YX50-F71V-00CW>
- Hadullo, K., Oboko, R., & Omwenga, E.. (2017). A model for evaluating e-learning systems quality in higher education in developing countries. *International Journal of Education and Development using ICT*, 13(2).
- Hobbs, B. F., Ludsin, S. A., Knight, R. L., Ryan, P. A., Biberhofer, J., & Ciborowski, J. J. (2002). Fuzzy cognitive mapping as a tool to define management objectives for complex ecosystems. *Ecological Applications*, 12(5), 1548-1565. [https://doi.org/10.1890/1051-0761\(2002\)012\[1548:FCMAAT\]2.0.CO;2](https://doi.org/10.1890/1051-0761(2002)012[1548:FCMAAT]2.0.CO;2)
- Hossain, S., & Brooks, L. (2008). Fuzzy cognitive map modelling educational software adoption. *Computers & Education*, 51(4), 1569-1588. <https://doi.org/10.1016/j.compedu.2008.03.002>
- Hu, P. J-H., & Hui, W.. (2012). Examining the role of learning engagement in technology-mediated learning and its effects on learning effectiveness and satisfaction. *Decision Support Systems*, 53(4), 782-792. <https://doi.org/10.1016/j.dss.2012.05.014>
- Huang, S., & Fang, N. (2013). Predicting student academic performance in an engineering dynamics course: A comparison of four types of predictive mathematical models. *Computers & Education*, 61, 133-145. <https://doi.org/10.1016/j.compedu.2012.08.015>
- Hughes, J. N, & Kwok, O. (2006). Classroom engagement mediates the effect of teacher-student support on elementary students' peer acceptance: A prospective analysis. *Journal of School Psychology*, 43(6), 465-480. <https://doi.org/10.1016/j.jsp.2005.10.001>
- Kaba, B., & Osei-Bryson, K-M. (2013). Examining influence of national culture on individuals' attitude and use of information and communication technology: Assessment of moderating effect of culture through cross countries study. *International Journal of Information Management*, 33(3), 441-452. <https://doi.org/10.1016/j.ijinfomgt.2013.01.010>
- Kahvandi, Z., Saghatforoush, E., ZareRavasan, A., & Mansouri, T. (2018). An FCM-based dynamic modelling of integrated project delivery implementation challenges in construction projects. *Lean Construction Journal*, 87, 63-87.
- Kashorda, M., & Waema, T. (2014). *E-readiness survey of Kenyan universities 2013 report*. Kenya Education Network.
- Kireev, V. S. (2016). Development of fuzzy cognitive map for optimizing e-learning course. *International Conference on Data Analytics and Management in Data Intensive Domains*. https://doi.org/10.1007/978-3-319-57135-5_4
- Kisanga, D. (2016). Determinants of teachers' attitudes towards e-learning in Tanzanian higher learning institutions. *International Review of Research in Open and Distributed Learning*, 17(5), 109-125. <https://doi.org/10.19173/irrodl.v17i5.2720>
- Kituyi, G. (2012). An analysis of e-learning information system adoption in Ugandan universities: Case of Makerere University Business School. *Information Technology Research Journal*, 2(1), 1-7.

- Knight, S., Gibson, A., & Shibani, A. (2020). Implementing learning analytics for learning impact: Taking tools to task. *The Internet and Higher Education*, 45, 100729. <https://doi.org/10.1016/j.iheduc.2020.100729>
- Kosko, B. (1986). Fuzzy cognitive maps. *International Journal of Man-Machine Studies*, 24(1), 65-75. [https://doi.org/10.1016/S0020-7373\(86\)80040-2](https://doi.org/10.1016/S0020-7373(86)80040-2)
- Kumar, A. N. V., & Uma, G. V. (2009). Improving academic performance of students by applying data mining technique. *European Journal of Scientific Research*, 34(4), 526-534.
- Kuo, F.-R., & Hwang, G.-J. (2015). A structural equation model to analyse the antecedents to students' web-based problem-solving performance. *Australasian Journal of Educational Technology*, 31(4), 400-420. <https://doi.org/10.14742/ajet.284>
- Lai, M. M., Lau, S. H., Mohamad Yusof, N. A., & Chew, K. W. (2015). Assessing antecedents and consequences of student satisfaction in higher education: evidence from Malaysia. *Journal of Marketing for Higher Education*, 25(1), 45-69. <https://doi.org/10.1080/08841241.2015.1042097>
- Lang, C., Siemens, G., Wise, A., & Gasevic, D. (2017). *Handbook of learning analytics: SOLAR, Society for Learning Analytics and Research*. <https://doi.org/10.18608/hla17>
- Lykourantzou, I., Giannoukos, I., Mpardis, G., Nikolopoulos, V., & Loumos, V. (2009). Early and dynamic student achievement prediction in e-learning courses using neural networks. *Journal of the American Society for Information Science and Technology*, 60(2), 372-380. <https://doi.org/10.1002/asi.20970>
- Macfadyen, L. P., & Dawson, S. (2010). Mining LMS data to develop an "early warning system" for educators: A proof of concept. *Computers & Education*, 54(2), 588-599. <https://doi.org/10.1016/j.compedu.2009.09.008>
- Makokha, G. L., & Mutisya, D. N. (2016). Status of e-learning in public universities in Kenya. *International Review of Research in Open and Distributed Learning*, 17(3), 341-359. <https://doi.org/10.19173/irrodl.v17i3.2235>
- Mansouri, T., Farasat, A., Menhaj, M. G., & Moghadam, M. R. S. (2011). Aro: A new model free optimization algorithm for real time applications inspired by the asexual reproduction. *Expert systems with Applications*, 38(5), 4866-4874. <https://doi.org/10.1016/j.eswa.2010.09.084>
- Masood, M. F., Khan, A., Hussain, F., Shaukat, A., Zeb, B., & Ullah, R. M. K. (2019). Towards the selection of best machine learning model for student performance analysis and prediction. *Proceedings of the 6th International Conference on Soft Computing & Machine Intelligence* (pp. 12-17). IEEE. <https://doi.org/10.1109/IS-CMI47871.2019.9004299>
- Meghji, A. F., Mahoto, N. A., Unar, M. A., & Shaikh, M. A. (2018). Analysis of student performance using EDM methods. *Proceedings of the 2018 5th International Multi-Topic ICT Conference* (pp. 1-7). IEEE. <https://doi.org/10.1109/IMTIC.2018.8467226>
- Misopoulos, F., Argyropoulou, M., & Tzavara, D. (2018). Exploring the factors affecting student academic performance in online programs: A literature review. In A. Khare & D. Hurst (Eds.), *On the line* (pp. 235-250). Springer. https://doi.org/10.1007/978-3-319-62776-2_18
- Mohammadi, M., Dawodi, M., Tomohisa, W., & Ahmadi, N. (2019). Comparative study of supervised learning algorithms for student performance prediction. *Proceedings of the 2019 International Conference on Artificial Intelligence in Information and Communication* (pp. 124-127). IEEE. <https://doi.org/10.1109/ICAIIIC.2019.8669085>
- Moridis, C. N., & Economides, A. A. (2009). Prediction of student's mood during an online test using formula-based and neural network-based method. *Computers & Education*, 53(3), 644-652. <https://doi.org/10.1016/j.compedu.2009.04.002>
- Muntean, C. I. (2011). Raising engagement in e-learning through gamification. *Proceedings of the 6th International Conference on Virtual Learning*, 323-329.
- Muuro, M. E., Wagacha, W. P., Kihoro, J., & Oboko, R. (2014). Students' perceived challenges in an online collaborative learning environment: A case of higher learning institutions in Nairobi, Kenya. *International Review of Research in Open and Distributed Learning*, 15(6), 132-161. <https://doi.org/10.19173/irrodl.v15i6.1768>

- Mwalumbwe, I., & Mtebe, J. S. (2017). Using learning analytics to predict students' performance in Moodle learning management system: A case of Mbeya University of Science and Technology. *The Electronic Journal of Information Systems in Developing Countries*, 79(1), 1-13. <https://doi.org/10.1002/j.1681-4835.2017.tb00577.x>
- Ngandu, M. R., & Brown, C. (2015, September). Influence of ideological contradictions when adopting ICTs to create authentic learning activities. *Conference on Emerging Technologies and Authentic Learning in Higher Vocational Education, Cape Town, South Africa*.
- Nownaisin, P., Chomsuwan, K., & Hongkraitert, N. (2012). Utilization of fuzzy cognitive map in modeling of Thailand science-based technology school. *Proceedings of IEEE International Conference on Teaching, Assessment, and Learning for Engineering*, T2D-5-T2D-7. <https://doi.org/10.1109/TALE.2012.6360392>
- Nwokeji, J. C., Stachel, R., & Holmes, T. (2019). Effect of instructional methods on student performance in flipped classroom. *Proceedings of the 2019 IEEE Frontiers in Education Conference*, 1-9. <https://doi.org/10.1109/FIE43999.2019.9028670>
- Pandey, H., & Singh, V. K. (2015). A fuzzy logic based recommender system for e-learning system with multi-agent framework. *International Journal of Computer Applications*, 122(17), 18-21. <https://doi.org/10.5120/21793-5140>
- Panigrahi, R., Srivastava, P. R., & Sharma, D. (2018). Online learning: Adoption, continuance, and learning outcome – A review of literature. *International Journal of Information Management*, 43, 1-14. <https://doi.org/10.1016/j.ijinfomgt.2018.05.005>
- Papageorgioua, E. I., & Kannappan, A. (2012). Fuzzy cognitive map ensemble learning paradigm to solve classification problems: Application to autism identification. *Applied Soft Computing*, 12(2), 3798-3809. <https://doi.org/10.1016/j.asoc.2012.03.064>
- Papamitsiou, Z., & Economides, A. A. (2014). Learning analytics and educational data mining in practice: A systematic literature review of empirical evidence. *Journal of Educational Technology & Society*, 17(4), 49-64.
- Pappas, C. (2019). *Top 20 elearning statistics for 2019: You need to know*. <https://elearningindustry.com/top-elearning-statistics-2019>
- Pardos, Z. A., Baker, R. S. J. D., San Pedro, M. O. C. Z., Gowda, S. M., & Gowda, S. M. (2013). Affective states and state tests: Investigating how affect throughout the school year predicts end of year learning outcomes. *Proceedings of the Third International Conference on Learning Analytics and Knowledge* (pp. 117-124). Association for Computing Machinery. <https://doi.org/10.1145/2460296.2460320>
- Peña, A., Sossa, H., & Gutierrez, F. (2007). Ontology agent based rule base fuzzy cognitive maps. In N. T. Nguyen, A. Grzech, R. J. Howlett, & L. C. Jain (Eds.), *Agent and Multi-Agent Systems: Technologies and Applications* (pp. 328-337). Springer. https://doi.org/10.1007/978-3-540-72830-6_34
- Pye, G., Holt, D., Salzman, S., Bellucci, E., & Lombardi, L. (2015). Engaging diverse student audiences in contemporary blended learning environments in Australian higher business education: Implications for design and practice. *Australasian Journal of Information Systems*, 19. <https://doi.org/10.3127/ajis.v19i0.1251>
- Queiros, D., & de Villiers, M. (2016). Online learning in a South African higher education institution: Determining the right connections for the student. *International Review of Research in Open and Distributed Learning*, 17(5), 165-185. <https://doi.org/10.19173/irrodl.v17i5.2552>
- Raga, R. C., & Raga, J. D. (2019). Early prediction of student performance in blended learning courses using deep neural networks. *Proceedings of the 2019 International Symposium on Educational Technology* (pp. 39-43). IEEE. <https://doi.org/10.1109/ISET.2019.00018>
- Raspopovic, M., Jankulovic, A., Runic, J., & Lucic, V. (2014). Success factors for e-learning in a developing country: A case study of Serbia. *International Review of Research in Open and Distributed Learning*, 15(3), 1-23. <https://doi.org/10.19173/irrodl.v15i3.1586>
- Romero-Zaldivar, V. A., Pardo, A., Burgos, D., & Kloos, C. D. (2012). Monitoring student progress using virtual appliances: A case study. *Computers & Education*, 58(4), 1058-1067. <https://doi.org/10.1016/j.compedu.2011.12.003>

- Ros, S., Hernández, R., Caminero, A., Robles, A., Barbero, I., Maciá, A., & Holgado, F. P. (2015). On the use of extended TAM to assess students' acceptance and intent to use third-generation learning management systems. *British Journal of Educational Technology*, 46(6), 1250-1271. <https://doi.org/10.1111/bjjet.12199>
- Roy, R., Potter, S., & Yarrow, K. (2004). Towards sustainable higher education: Environmental impacts of conventional campus, print-based and electronic/open learning systems. In D. Murphy, R. Carr, J. Taylor, & T. M. Wong (Eds.), *Distance education & technology: Issues and practice* (pp. 129-145). Open University of Hong Kong Press.
- Salinas, E. Y., Williams, A. E., & King, C. E. (2019). Effect of controlling group heterogeneity on student performance in a graphical programming course. *Proceedings of the 2019 IEEE Frontiers in Education Conference*, 1-8. <https://doi.org/10.1109/FIE43999.2019.9028593>
- Salmeron, J. L. (2009). Augmented fuzzy cognitive maps for modelling LMS critical success factors. *Knowledge-Based Systems*, 22(4), 275-278. <https://doi.org/10.1016/j.knosys.2009.01.002>
- Salmeron, J. L., & Froelich, W. (2016). Dynamic optimization of fuzzy cognitive maps for time series forecasting. *Knowledge-Based Systems*, 105, 29-37. <https://doi.org/10.1016/j.knosys.2016.04.023>
- Salmeron, J. L., Mansouri, T., Moghadam, M. R. S., & Mardani, A. (2019). Learning fuzzy cognitive maps with modified asexual reproduction optimisation algorithm. *Knowledge-Based Systems*, 163, 723-735. <https://doi.org/10.1016/j.knosys.2018.09.034>
- Sharma, S. K., Gaur, A., Saddikuti, V., & Rastogi, A. (2017). Structural equation model (SEM)-neural network (NN) model for predicting quality determinants of e-learning management systems. *Behaviour & Information Technology*, 36(10), 1053-1066. <https://doi.org/10.1080/0144929X.2017.1340973>
- Sheshadri, A., Gitinabard, N., Lynch, C. F., Barnes, T., & Heckman, S. (2018). Predicting student performance based on online study habits: A study of blended courses. *Proceedings of the 2018 International Conference on Educational Data Mining*, 411-417.
- Siegle, D., Rubenstein, L. D. V., Pollard, E., & Romey, E.. (2010). Exploring the relationship of college freshmen honors students' effort and ability attribution, interest, and implicit theory of intelligence with perceived ability. *Gifted Child Quarterly*, 54(2), 92-101. <https://doi.org/10.1177/0016986209355975>
- Siemens, G., & Long, P. (2011). Penetrating the fog: Analytics in learning and education. *EDUCAUSE Review*, 46(5), 30.
- Ssekakubo, G., Suleman, H., & Marsden, G. (2011). Issues of adoption: Have e-learning management systems fulfilled their potential in developing countries? *Proceedings of the South African Institute of Computer Scientists and Information Technologists Conference on Knowledge, Innovation and Leadership in a Diverse, Multidisciplinary Environment* (pp. 231-238). Association for Computing Machinery. <https://doi.org/10.1145/2072221.2072248>
- Sweta, S., & Lal, K. (2016). Learner model for automatic detection of learning style using FCM in adaptive e-learning system. *IOSR Journal of Computer Engineering*, 18(2), 18-24.
- Takács, M., Rudas, I. J., & Lantos, Z. (2014). Fuzzy cognitive map for student evaluation model. *IEEE International Conference on System Science and Engineering*, 284-288. <https://doi.org/10.1109/ICSSE.2014.6887950>
- Tarus, J. K., Gichoya, D., & Muumbo, A. (2015). Challenges of implementing e-learning in Kenya: A case of Kenyan public universities. *International Review of Research in Open and Distributed Learning*, 16(1), 120-141. <https://doi.org/10.19173/irrodl.v16i1.1816>
- Thai-Nghe, N., Busche, A., & Schmidt-Thieme, L. (2009). Improving academic performance prediction by dealing with class imbalance. *Proceedings of the Ninth International Conference on Intelligent Systems Design and Applications* (pp. 878-883) IEEE. <https://doi.org/10.1109/ISDA.2009.15>
- Thai-Nghe, N., Drumond, L., Krohn-Grimberghe, A., & Schmidt-Thieme, L. (2010). Recommender system for predicting student performance. *Procedia Computer Science*, 1(2), 2811-2819. <https://doi.org/10.1016/j.procs.2010.08.006>
- Thai-Nghe, N., Horv, T., & Schmidt-Thieme, L. (2011). Personalized forecasting student performance. *Proceedings of the 11th International Conference on Advanced Learning Technologies* (pp. 412-414). IEEE. <https://doi.org/10.1109/ICALT.2011.130>

- Thai-Nghe, N., Horváth, T., & Schmidt-Thieme, L. (2012). Factorization models for forecasting student performance. In O. Santos, & J. Boticario (Eds.). *Educational recommender systems and technologies: Practices and challenges* (pp. 129-153). IGI Global. <https://doi.org/10.4018/978-1-61350-489-5.ch006>
- Toscher, A., & Jahrer, M. (2010). Collaborative filtering applied to educational data mining. *Proceedings of KDD Cup*.
- Tsadiras, A., & Stamatis, D. (2008). Decisions on networked learning based on fuzzy cognitive maps. *Proceedings of the 6th International Conference on Networked Learning*, 376-383.
- Turabieh, H. (2019). Hybrid machine learning classifiers to predict student performance. *Proceedings of the 2nd International Conference on New Trends in Computing Sciences*. IEEE. <https://doi.org/10.1109/IC-TCS.2019.8923093>
- Umer, R., Susnjak, T., Mathrani, A., & Suriadi, S. (2018). A learning analytics approach: Using online weekly student engagement data to make predictions on student performance. *Proceedings of the 2018 International Conference on Computing, Electronic and Electrical Engineering*. IEEE. <https://doi.org/10.1109/ICECUBE.2018.8610959>
- van Vliet, M., Kok, K., & Veldkamp, T. (2010). Linking stakeholders and modellers in scenario studies: The use of fuzzy cognitive maps as a communication and learning tool. *Futures*, 42(1), 1-14. <https://doi.org/10.1016/j.futures.2009.08.005>
- Vialardi, C., Chue, J., Peche, J. P., Alvarado, G., Vinatea, B., Estrella, J., & Ortigosa, A. (2011). A data mining approach to guide students through the enrollment process based on academic performance. *User Modeling and User-Adapted Interaction*, 21(1-2), 217-248. <https://doi.org/10.1007/s11257-011-9098-4>
- Yang, F., Li, F. W. B., & Lau, R. W. H. (2011). Fuzzy cognitive map based student progress indicators. In H. Leung, E. Popescu, Y. Cao, R. W. H. Lau, & W. Nejdl (Eds.). *Advances in web-based learning*. Springer. https://doi.org/10.1007/978-3-642-25813-8_19
- Yesil, E., Ozturk, C., Dodurka, M. F., & Sahin, A. (2013). Control engineering education critical success factors modeling via fuzzy cognitive maps. *Proceedings of the 12th International Conference on Information Technology Based Higher Education and Training*. IEEE. <https://doi.org/10.1109/ITHET.2013.6671061>
- Yu, H-F, Lo, H-Y, Hsieh, H-P, Lou, J-K, McKenzie, T. G., Chou, J-W, Chung, P-H., Ho, C-H., Chang, C-F, Wei, Y-H, Weng, J-Y, Yan, E-S, Chang, C-W, Kuo, T-T, Lo, Y-C., Chang, P. T., Po, C., Wang, C-Y, Huang, Y-H. ... C-J. Lin. (2010). Feature engineering and classifier ensemble for KDD Cup 2010. *Journal of Machine Learning Research: Workshop and Conference Proceedings*, 1, 1-16.
- ZareRavasan, A., Amani, M., & Ashrafi, A. (2018). E-learning systems and its outcomes: The moderating role of perceived compatibility. *IT Management Studies*, 6(24), 87-107.
- ZareRavasan, A., & Ashrafi, A. (2019). Influencing factors on students' continuance intention to use Learning Management System (LMS). *Proceedings of the 9th International Conference on Information Communication and Management* (pp. 165-169). Association for Computing Machinery. <https://doi.org/10.1145/3357419.3357429>
- ZareRavasan, A., & Mansouri, T. (2014). A FCM-based dynamic modeling of ERP implementation critical failure factors. *International Journal of Enterprise Information Systems*, 10(1), 32-52. <https://doi.org/10.4018/ijeis.2014010103>
- ZareRavasan, A., & Mansouri, T. (2016). A dynamic ERP critical failure factors modelling with FCM throughout project lifecycle phases. *Production Planning & Control*, 27(2), 65-82. <https://doi.org/10.1080/09537287.2015.1064551>
- Zhang, W., & Cheng, Y. L. (2012). Quality assurance in e-learning: PDPP evaluation model and its application. *The International Review of Research in Open and Distributed Learning*, 13(3), 66-82. <https://doi.org/10.19173/irrodl.v13i3.1181>
- Zhu, C. (2012). Student satisfaction, performance, and knowledge construction in online collaborative learning. *Journal of Educational Technology & Society*, 15(1), 127-136.

APPENDIX A. THE MEASUREMENT ITEMS USED FOR DATA GATHERING

Measurement items	Sources
Part A*	
Course Characteristics (CC)	
CC1. Course plan (syllables and course assessment method) CC2. List of textbooks/ references CC3. List (and CV) of lecturer(s) CC4. List (and CV) of teaching assistant(s) CC5. Quality learning material CC6. Interactive/Gamified learning material	(Hadullo et al., 2017; Tarus et al., 2015)
LMS Characteristics (LMS)	
LMS1. Perceived usefulness LMS2. Perceived ease of use LMS3. Perceived enjoyment LMS4. Perceived LMS system quality (Reliability, availability, response time, ...)	(Kaba & Osei-Bryson, 2013; Panigrahi et al., 2018; Ros et al., 2015; Sharma et al., 2017)
Student Characteristics (SC)	
SC1. Attitude SC2. Self-efficacy SC3. motivation, incentives SC4. experience SC5. Self-regulation	(Al-Azawei et al., 2016; Hadullo et al., 2017; Hwang, 2015; Kisanga, 2016; Kuo & Kituyi, 2012; Makokha & Mutisya, 2016; Panigrahi et al., 2018)
Student Support (SS)	
SS1. Interactions with peers SS2. Interactions with teaching assistants SS3. Interactions with lecturer(s) SS4. Assignment feedback SS5. Exam feedback SS6. Technical support for LMS and Virtual Classes with convenient operating hours SS7. Subjective Norm	(Baloyi, 2014a, 2014b; Chawinga & Zozie, 2016; Makokha & Mutisya, 2016; Muuro et al., 2014; Panigrahi et al., 2018; Queiros & de Villiers, 2016)
Institutional Factors (IF)	
IF1. Perceived quality of maintenance of infrastructure, seminars, and workshops IF2. Perceived quality of institutional infrastructure IF3. Perceived quality of institutional hardware and software	(Hadullo et al., 2017; Kashorda & Waema, 2014; Ngandu & Brown, 2015; Ssekakubo et al., 2011; Tarus et al., 2015)
Overall Performance (OP)	
OP1. User satisfaction score OP2. Knowledge construction level OP3. Student GPA (Grade Point Average)	(Ferguson & DeFelice, 2010; Lai et al., 2015; Misopoulos et al., 2018; Raspopovic et al., 2014; Zhang & Cheng, 2012; Zhu, 2012)

Measurement items	Sources
Part B*	
Student Engagement (SE)	
SE1. Total studying time in LMS (min) SE2. Total login frequency in LMS SE3. Number of discussion posts views SE4. Number of resources viewed SE5. Number of course page views SE6. Average time per session (min) SE7. Total time online (min) SE8. Numbers of links viewed SE9. Number of content page views SE10. The regularity of learning interval in LMS SE11. Total number of discussion posts SE12. Average assessment quiz grade	(Dias et al., 2015; Hadullo et al., 2017)

* Seven point Likert scale (strongly low to strongly high) for all measurement items of Part A (excluding OP3: GPA) is used; Data for Part B is extracted from Moodle LMS at the end of each semester

APPENDIX B. INTERRELATIONS AMONG VARIABLES

Appendix B can be downloaded from <https://doi.org/10.28945/4760> or from <https://www.informing-science.org/Publications/GetFile/6977?ArticleFileID=7639>

AUTHORS



Taha Mansouri is a Postdoc Researcher at the School of Science, Engineering, and Environment, the University of Salford, Manchester, UK. He has published in acclaimed journals, such as the Knowledge-Based Systems, Expert Systems with Applications, Applied Soft Computing, Optic Letters, and Telecommunication Systems. His research interests include Machine Learning, Deep Learning, Reinforcement Learning, Computer Vision, and Complex Systems Modelling.



Ahad ZareRavasan is an Assistant Professor at the Department of Corporate Economy, Faculty of Economics and Administration Masaryk University, Brno, Czech Republic. He has published in acclaimed journals, such as the International Journal of Information Management, Expert Systems with Applications, Information Systems, International Journal of Production Research, Journal of Business and Industrial Marketing, and the Journal of Enterprise Information Management. His research interests include Information Systems, e-learning, Business Analytics, and Blockchain.



Amir Ashrafi is currently a Ph.D. student of business & management in the Alliance Manchester Business School at the University of Manchester. He has published a number of papers in acclaimed journals, such as the International Journal of Information Management, Journal of Enterprise Information Management, Journal of Business and Industrial Marketing, Interactive Learning Environment, and Journal of Organizational and End User Computing. His research focuses on Digital Innovation & Transformation, Big data analytics, Artificial Intelligence, and IT Business Value.