International Journal of Computers in Education
2024, Volume 7, Issue 2, 71-82
Research Article

Exploring the Transitions of Online Engagement Through Learning Analytics with Markov Modelling with Elementary Education Pre-Service Teachers

Nilüfer Atman Uslu [1] *, Feriştah Dalkılıç [1]

[1] Dokuz Eylül University, Türkiye.

Abstract – This paper provides a learning analysis based on system navigation to expand on the changes in their interactions with online learning systems over time. By providing an analysis of their participation and communication logs, this research aims to shed light on how they communicate with global learning systems and how these patterns are illuminated over time. The study was conducted with students in the elementary education department at a state university in the fall semester of the 2023-2024 academic year. Fifty-seven undergraduate students who actively participated in the Fundamentals of Computer Science course participated in the study. This study used Moodle data from the Fundamentals of Computer Science course for 14 weeks. Weekly learning content and materials in various formats have been uploaded to the system by the instructor. For each course, students were required to review different learning materials uploaded by the instructor and completely different learning task. Student's behavioral patterns will be examined in terms of the time they spend in the course, the time they spend on the content and the frequency with which they access the course content. Markov Chains have been applied to model online browsing behavior with time-varying variables. The findings show that the Markov chain for time spent, revealing the transition probabilities between engagement states at T1 and T2. The analysis indicates that students in the Low engagement group at T1 have a 50% probability of remaining in the Low cluster at T2, while also demonstrating a 50% chance of transitioning to the High cluster. Conversely, students in the High engagement group at T1 exhibit an 83% probability of staying in the High cluster at T2, with a 17% likelihood of moving to the Low cluster. Furthermore, the Markov chain for visit course, emphasizing the transition probabilities for students between engagement clusters at T1 and T2. It reveals that students initially in the High engagement group have an 83% probability of remaining in the High cluster at T2, while also indicating a 17% likelihood of transitioning to the Low cluster. On the other hand, students in the Low engagement group at T1 display a 50% probability of moving to the High cluster at T2, alongside a 65.5% chance of remaining in the Low cluster.

Keywords: Elementary Education, Pre-service Teachers, Behavioral pattern, Markov chain, Learning analytics.

Introduction

Over the last 20 years, online learning solutions have become increasingly used in higher education (Yildiz Durak, 2019, 2023). Especially during an emergency remote teaching process with the COVID-19 crisis, many faculty members faced the challenge of designing online learning and teaching processes (Perifanou et al., 2022; Uslu & Durak, 2022; Yong et al., 2021). One of these difficulties was related to the need for sustaining learners' cognitive, emotional and behavioral engagement (Khalif et al., 2021). Although online learning environments have many potentials, such as flexibility and not being bound to time and place, they have brought problems, such as the inability to track learning and student behavior in virtual classrooms. Thus, learning designers and researchers need to have a better understanding of online learning experiences (Kokoç et al., 2021). At this point, it is crucial to keep in mind that student engagement is not desired level compared to in-person learning (F. Martin & Borup, 2022). This situation has created the necessity of using the data collected in online learning environments to understand the nature of engagement.

* Corresponding author: Dokuz Eylül University Buca Faculty of Education, Türkiye.
e-mail addresses: atmanuslu@gmail.com, feristah@cs.deu.edu.tr

https://doi.org/10.5281/zenodo.14580877
Received 3 March 2024; Accepted 11 Jul 2024
ISSN: 2636-8722.

In recent years, the widespread use of online platforms and digital technologies has generated a wealth of data on user behaviors in online learning environments. Smart technology-enhanced platforms, such as learning management systems, capture interaction logs, clickstream data, performance parameters, and more (Abebe et al., 2019). One of the common tools used as an online learning solution in higher education is learning management systems. Despite the prevalence of use, instructors need the option to monitor student behavior in online courses, their interaction with the content, and their engagement in the learning process (Mubarak et al., 2020). On the other hand, examining student logs and interaction-related learning analytics can provide critical information in predicting drop-out from the course (Mubarak et al., 2020) tracking learning consistency (Zhou & Bhat, 2021), examining motivation (Wang & Chih-Yuan, 2022) and understanding students' learning paths.

In this way, log-data has the potential to bring insightful knowledge about learner engagement. However, studies on student engagement mostly focus on in-person learning environments and do not consider the restrictions imposed by online environments (F. Martin & Borup, 2022). Analyzing log data with Markov chain models and examining changes over time of engagement is crucial for designing compelling learning experiences. In analyzing learner patterns, the Markov chain captures the probabilistic transitions between different states.

In the following sections, we will provide an overview of the theoretical foundations of online engagement discuss relevant literature and explain how to apply Markov Chain Model to studying online behavioral patterns. Our research can contribute to data-driven decision-making and user behavior analysis in online environments.

Engagement

Engagement defined as the psychological state of students being activated, putting in effort, and being absorbed during learning activities (Wong & Liem, 2022). As a result of a meta-analysis study, learner engagement was found to have a moderately strong and positive correlation with academic achievement (Lei et al., 2018). Schnitzler et al. (2021), found that students who demonstrated higher participation patterns systematically achieved greater end-of-year gains than those who demonstrated lower participation. Engagement is accepted as an essential construct in literature. Several educational psychologists have developed models and perspectives on this structure's definition, dimensions, and nature (Ben-Eliyahu et al., 2018; Lam et al., 2014; A. J. Martin, 2007; Skinner et al., 2009). Accordingly, the conceptual uncertainty of engagement is considered a multidimensional construct (F. Martin & Borup, 2022; Wong & Liem, 2022). These dimensions are considered as affective, behavioral, and cognitive (Pentaraki & Burkholder, 2017; Wong & Liem, 2022). Emotional engagement is defined as how active students feel during learning activities (Wong & Liem, 2022). Behavioral engagement encompasses the observable actions students take to be on-task and exert effort, as well as their attendance and involvement in a course (Reeve et al., 2020; Pentaraki & Burkholder, 2017) Cognitive engagement is the effort made to enhance one's cognitive processes to comprehend the material being learned or to overcome barriers to academic advancement (Reeve et al., 2020; Vezne et al., 2023). Cognitive engagement demonstrates a keen interest in learning, exceeding the basic course requirements and possibly even redefining the parameters of assignments (Pentaraki & Burkholder, 2017). In this case, behavioral engagement relates to the "directing" aspect of attention or the intentional use of attentional effort, as opposed to cognitive engagement, which relates to a "state of consciousness (Wong & Liem, 2022).

When switching from face-to-face environments to online learning processes, engaging students brings with it many challenges. According to Martin and Borup (2022), the online environment changes the way students engage in learning activities and can introduce different barriers and demands that make cognitive engagement and self-regulation particularly challenging for some students. The affective component of engagement in online environments has indicators such as setting and maintaining realistic goals, expressing underlying beliefs, identifying driving forces, dedicating oneself to gaining knowledge (Redmond et al., 2018). Behavioral engagement is defined as the physical behaviors and energy that students display while completing learning activities (F. Martin & Borup, 2022). In online environments, students who show cognitive engagement are characterized by features such as analyzing thoughtfully, engaging in self-awareness, combining concepts, fostering comprehensive knowledge (Redmond et al., 2018).

Engagement and Learning Analytics

Learning analytics (LA) is a workflow that involves collecting and analyzing large amounts of data from learning environments (Sun et al., 2018). LA aims to enhance learning and teaching by analyzing students' behaviors, providing insights for teachers to improve their instruction and guide students in adjusting their learning behaviors (Huang et al., 2020). LA primarily uses log data, which contains records of learner activity in educational contexts. Log data can include a variety of factors, such as counts of clicks or page views, time spent on a particular action, keyboard strokes, results of an activity, and counts of other activities (Henrie et al., 2018). Log-data is used for purposes such as predicting student success (Hasan et al., 2020; (Huang et al., 2020; Riestra-González et al., 2021), supporting learning regulation (Sedrakyan et al., 2020), identifying students at risk (Foster & Siddle, 2020; Queiroga et al., 2022), facilitating educators' decision-making processes (Gutiérrez et al., 2020). Log data serves as an activity-level scalable measure, capturing real-time user interactions while being minimally disruptive and automatically tracked behind the scenes (Henrie et al., 2018). Log data can also be used to identify individuals' engagement patterns. According to Martin and Borup (2022), engagement of the learner can be viewed as interaction "with" others and materials or "through" activities and experiences, including involvement with courseware, peers, and the instructor, as well as participation in collaboration, communication, and presence. In this way, log-data has the potential to retrieve insightful conclusions for understanding learning engagement.

Modeling Longitudinal Transitions of Engagement

Learning engagement is a flexible state influenced by both student and activity characteristics, operating on multiple levels within different learning contexts and time frames, with moment-to-moment engagement influencing overall and long-term engagement (Wong & Liem, 2022). In this case, a multi-state Markov chain model is a useful tool for describing a process in which an entity transitions between a limited number of distinct states. Also, individuals differ in their engagement with digital technologies, regardless of their level of digital skills (Bergdahl et al., 2020). Accordingly, with Markov Chain, individual differences can also be identified. Markov chains are used to represent a series of random variables that correspond to the different states of a system, with each state being dependent only on the previous state (Teugels, 2008). Markov chain models are used in text prediction and speech recognition (He & Dong, 2020), stock market and financial modeling (Trichilli et al., 2020), weather forecasting (Yutong, 2021), genetics and bioinformatics (Khodaei et al., 2021) epidemiology and disease modeling (Tada et al., 2019), traffic flow and transportation planning (Besenczi et al., 2021), quality control and manufacturing (Papadopoulos et al., 2019), game theory and decision-making (Ye et al., 2020). In addition to these areas, Markov Chain models are used in the field of education and especially in online learning. Polyzou et al. (Polyzou et al., 2019) used Markov Chain based framework to empower student choices by recommending courses based on sequential relationships and prior courses. Vatsalan et al. (2022) focused on privacy risk quantification and proposed a method using a Markov Model (MM) to quantify re-identification risks by considering event-level information and correlation between attributes. Kokoç et al. (2021), examined students' online assignment submission patterns using and time-dependent changes in university students' submission behavior by employing by Markov Chains. They found that exhibited consistent patterns in their assignment submission remained relatively stable over time. More recently, Hilpert et al. (2023) used log-data with Markov Chain to retrieve changes in students' transitions in self-regulated learning behaviors. They also found that the dynamic aspects of self-regulated behaviors were significant predictors of student achievement. In conclusion, although early studies have used Markov Chain models to analyze student log data, there is a need for further research to explore its application in understanding the nature of student engagement.

The Purpose of The Study

The current study provides a learning analysis based system navigation to expand on the changes in users'? interactions with online learning systems over time. By providing an analysis of their engagement and communication logs, this research aims to shed light on how they communicate with global learning systems and how these patterns are illuminated over time. Therefore, we formulated the following research questions:

RQ1: What behavioral patterns do students show in an LMS system?
RQ2: How do students' behavioral patterns transition over time?

We propose to investigate online behavioral patterns using Markov chain modeling and temporal learning analytics together. By analyzing temporal dynamics, we aim to capture the evolution of user behavior over time and gain meaningful insights that can inform decision-making in various areas. This approach can contribute to developing more effective and personalized digital experiences by increasing our knowledge of user engagement and interaction patterns in online environments.

Method

Participants and Context

The study was conducted with students in the elementary education department at a state university in the fall semester of the 2023-2024 academic year. Fifty-seven undergraduate students who actively participated in the Fundamentals of Computer Science course participated in the study. The course includes conceptual definitions of basic concepts of computer science, algorithms and programming, artificial intelligence, and blockchain technologies. All students participating in this study were enrolled in the course. The Edwiser Pro plug-in in Moodle recorded learning analytics by monitoring student navigation. Weekly learning content and materials in various formats have been uploaded to the system by the instructor. For each course, students were required to review different learning materials uploaded by the instructor and completely different learning tasks. Students freely used the course environment to post learning tasks, questions, and discussions and to communicate with their peers. Each student has displayed their course activity status on their profile. Students also had the opportunity to see a list of their classmates in the course and view their profiles. Students could see the success status and feedback of their learning tasks. Student's behavioral patterns will be examined in terms of the time they spend in the course, the time they spend on the content and the frequency with which they access the course content.

Data Analysis

Moodle automatically recorded students' browsing behavior. These data have identified necessary online learning behavior to represent students' behavior in LMS. This study retrieves the number of clicks students had with each content and LMS module. Additionally, the relationships between clicks were analyzed. Thus, structures can be created in which the navigation behavior of the individual can be modeled. At this point, Markov Chains have been applied to model online browsing behavior with time-varying variables. This method is a person-centered method that captures qualitative differences in response patterns of navigations over time.

We defined two time points for each of the students, the middle, and the end of the semester. The overall data analysis process was given in Figure 1.

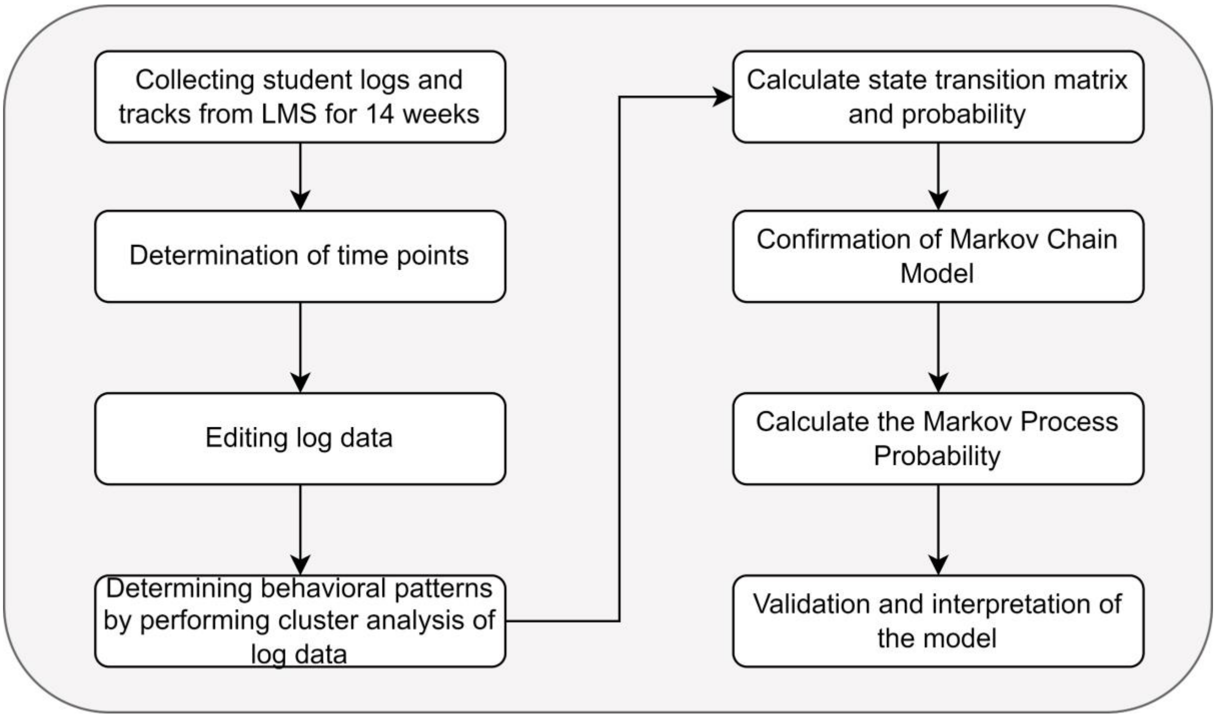

Fig. 1. Analytic Procedure

According to Figure 1, data analysis started with collecting data from students for 14 weeks. After time points were determined, log data was made ready for analysis. Behavior patterns were extracted by analyzing log data with cluster analysis. Thus, the state transition matrix and probabilities were calculated. After the model was verified and Markov probabilities were calculated, the model was validated and interpreted.

Findings

It was investigated whether students' online engagement behaviors changed in terms of time spent in the course and number of visits to the course according to two time points determined in the 14-week period in the online learning environment (T: 0-7 weeks; T2: 8-14 weeks). Findings showing change over time are presented in Figure 2 and Figure 3. According to Figure 2 and Figure 3, there are transitions between low-high, high-low and high-high.

Figure 2. Time change graph - Time spent.

In Figure 2, the low level generally transitions to high depending on the time spent. In Figure 3, the low level generally transitions to a high level, depending on the number of visits to the course.

Figure 3. Time change chart - visit course

Markov Chain was used to analyze the transitions between engagement states at two time points in more detail. Students were grouped as High and Low according to the learning analytics data in the system at 2 time points. The calculated values for their transitions are presented in Figure 4 and Figure 5. Markov Chain analysis shows real transition probabilities.

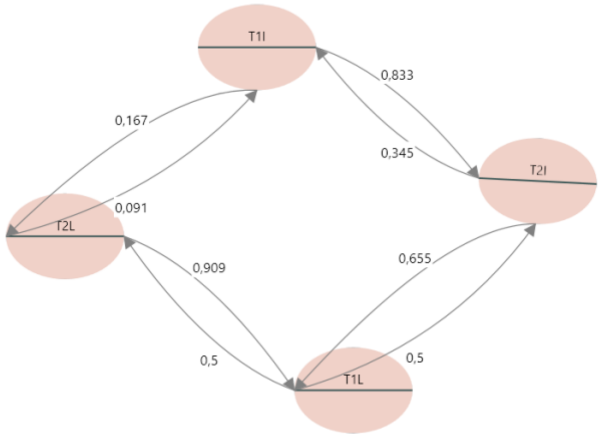

Figure 4. Markov chain for time spent
***T1L:** Time 1 Low; **T1I:** Time 1 High; **T2L:** Time 2 Low; **T2I:** Time 2 High.*

The arrow between groups indicates the direction of the transition. Numerical values indicate the transition probability between each group. The maximum probability of each transition is 1 (i.e. 100%). The Markov chains presented in Figure 3 show that the transition probability of students whose engagement level is in the low group at T1 time point to be in the low cluster at T2 is 0.5 (that is, 50 out of 100 students), and the probability of being in the high cluster is 0.50. It shows that the transition probability of students whose engagement level is in the high group at T1 time point to be in the high cluster at T2 point is 0.833 (83%), and the probability of being in the low cluster is 0.167.

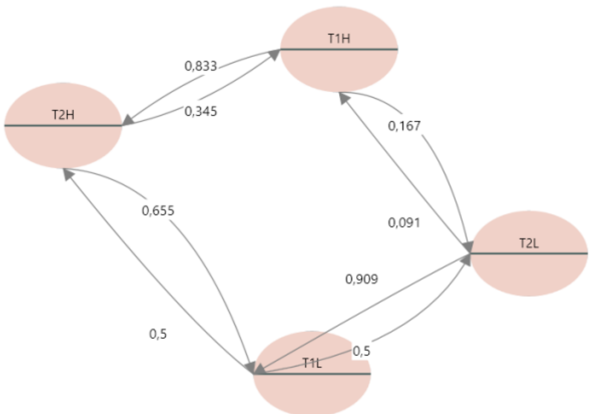

Figure 5. Markov chain for visit course

According to Figure 4, the transition probability of students whose engagement level is in the high group at T1 time point to be in the high cluster at T2 point will be 0.833, and the probability of being in the low cluster will be 0.167. The probability of students in the low group at T1 being in the high cluster at T2 will be 0.5, and the probability of being in the low cluster will be 0.655.

Conclusion, Discussion and Suggestions

The findings presented in this study shed light on the dynamics of student engagement transitions over two time points using Markov Chain analysis. The analysis categorized students into High and Low engagement states based on learning analytics data and examined the transitions between these states. The results provide valuable insights into the probabilities associated with these transitions.

The findings show that the Markov chain for time spent, revealing the transition probabilities between engagement states at T1 and T2. The analysis indicates that students in the Low engagement group at T1 have a 50% probability of remaining in the Low cluster at T2, while also demonstrating a 50% chance of transitioning to the High cluster. Conversely, students in the High engagement group at T1 exhibit an 83% probability of staying in the High cluster at T2, with a 17% likelihood of moving to the Low cluster. These results underscore the persistence of engagement states over time and highlight the tendency for students to maintain their initial levels of engagement. These results highlight the dynamics of student engagement over time and show that although there is a certain amount of transitivity between different levels of engagement, there is also a clear continuum. The fact that students who were in the Low engagement group at T1 tended to remain in the Low cluster at T2 with 50% probability could be due to extrinsic factors such as lack of motivation, lack of interest or insufficient support. Likewise, the fact that students who were in the High engagement group at T1 were 83% likely to remain in the High cluster at T2 may indicate that these students were able to maintain their engagement level due to factors such as intrinsic motivation, effective study habits or supportive environments. However, the fact that 50% of students in the Low engagement group were able to move to the High cluster and 17% of students in the High engagement group moved to the Low cluster suggests that student engagement is somewhat variable and can be improved over time through various interventions. These results emphasize that student engagement levels tend to persist over time and that students tend to maintain their initial levels.

Furthermore, the Markov chain for visit course, emphasizing the transition probabilities for students between engagement clusters at T1 and T2. It reveals that students initially in the High engagement group have an 83% probability of remaining in the High cluster at T2, while also indicating a 17% likelihood of transitioning to the Low cluster. On the other hand, students in the Low engagement group at T1 display a 50% probability of moving to the High cluster at T2, alongside a 65.5% chance of remaining in the Low cluster. These findings suggest a degree of fluidity in student engagement levels, with a notable proportion of students transitioning between clusters over time. There may be various reasons for this transitivity. Students' motivation levels and interests may change over time; course content or teaching methods may affect students' level of engagement. External stressors that affect student learning can also cause fluctuations in engagement levels. Support services and resources provided at school or at home, innovative and student-centered teaching methods, regular assessment and feedback, participatory learning environments such as group work and projects can increase a student's level of engagement. Students' learning styles, study habits and self-regulation skills may also change over time and affect their level of engagement. These findings suggest that more targeted interventions and strategies should be developed to increase student engagement. Markov Chain analyses provide important insights into understanding the interaction trends of specific groups of students over time and designing appropriate interventions to address these trends.

The findings of this study have significant implications for educators, administrators, and policymakers. Understanding the dynamics of student engagement transitions is crucial for developing targeted interventions and support systems. By recognizing the persistence of engagement states over time, educational institutions can tailor their strategies to maintain and enhance student engagement. Additionally, the observed fluidity in student engagement levels highlights the need for adaptable and responsive approaches to support students as they transition between engagement clusters.

While the Markov Chain analysis provides valuable insights, it is essential to acknowledge its limitations. The analysis is based on predefined High and Low engagement states, which may oversimplify the complexity of student engagement. Furthermore, the study focuses on transition probabilities at two specific time points, potentially overlooking the nuances of engagement fluctuations within shorter intervals. Additionally, the analysis relies on learning analytics data, which may not capture the full spectrum of student engagement, potentially limiting the generalizability of the findings.

Based on the study's findings, it is recommended that educational institutions implement targeted interventions to support students in maintaining or transitioning to higher engagement levels. These interventions could include personalized academic support, mentorship programs, and tailored feedback mechanisms to address the specific needs of students in different engagement clusters. Moreover, future research should consider incorporating qualitative data to complement the quantitative analysis, providing a more comprehensive understanding of student engagement dynamics. Additionally, longitudinal studies tracking engagement transitions over multiple time points can offer deeper insights into the evolving nature of student engagement. Finally, efforts to enhance the granularity and accuracy of learning analytics data can improve the precision of transition probabilities and enable more robust conclusions.

References

Abebe, B. T., Weiss, M., Modess, C., Roustom, T., Tadken, T., Wegner, D., Schwantes, U., Neumeister, C., Schulz, H., Scheuch, E., al., et, Abu-Saad, K., Murad, H., Barid, R., Olmer, L., Ziv, A., Younis-Zeidan, N., Kaufman-Shriqui, V., Gillon-Keren, M., … Masha'al, D. (2019). Mindfulness virtual community. *Trials*, *17*(1).

Ben-Eliyahu, A., Moore, D., Dorph, R., & Schunn, C. D. (2018). Investigating the multidimensionality of engagement: Affective, behavioral, and cognitive engagement across science activities and contexts. *Contemporary Educational Psychology*, *53*. https://doi.org/10.1016/j.cedpsych.2018.01.002

Bergdahl, N., Nouri, J., & Fors, U. (2020). Disengagement, engagement and digital skills in technology-enhanced learning. *Education and Information Technologies*, *25*(2). https://doi.org/10.1007/s10639-019-09998-w

Besenczi, R., Bátfai, N., Jeszenszky, P., Major, R., Monori, F., & Ispány, M. (2021). Large-scale simulation of traffic flow using Markov model. *PLoS ONE*, *16*(2 February). https://doi.org/10.1371/journal.pone.0246062

Foster, E., & Siddle, R. (2020). The effectiveness of learning analytics for identifying at-risk students in higher education. *Assessment and Evaluation in Higher Education*, *45*(6). https://doi.org/10.1080/02602938.2019.1682118

Gutiérrez, F., Seipp, K., Ochoa, X., Chiluiza, K., De Laet, T., & Verbert, K. (2020). LADA: A learning analytics dashboard for academic advising. *Computers in Human Behavior*, *107*. https://doi.org/10.1016/j.chb.2018.12.004

Hasan, R., Palaniappan, S., Mahmood, S., Abbas, A., Sarker, K. U., & Sattar, M. U. (2020). Predicting student performance in higher educational institutions using video learning analytics and data mining techniques. *Applied Sciences (Switzerland)*, *10*(11). https://doi.org/10.3390/app10113894

He, Y., & Dong, X. (2020). Real time speech recognition algorithm on embedded system based on continuous Markov model. *Microprocessors and Microsystems*, *75*. https://doi.org/10.1016/j.micpro.2020.103058

Henrie, C. R., Bodily, R., Larsen, R., & Graham, C. R. (2018). Exploring the potential of LMS log data as a proxy measure of student engagement. *Journal of Computing in Higher Education*, *30*(2). https://doi.org/10.1007/s12528-017-9161-1

Hilpert, J. C., Greene, J. A., & Bernacki, M. (2023). Leveraging complexity frameworks to refine theories of engagement: Advancing self-regulated learning in the age of artificial intelligence. *British Journal of Educational Technology*, *54*(5). https://doi.org/10.1111/bjet.13340

Huang, A. Y. Q., Lu, O. H. T., Huang, J. C. H., Yin, C. J., & Yang, S. J. H. (2020). Predicting students' academic performance by using educational big data and learning analytics: evaluation of classification methods and learning logs. *Interactive Learning Environments*, *28*(2). https://doi.org/10.1080/10494820.2019.1636086.

Khlaif, Z. N., Salha, S., & Kouraichi, B. (2021). Emergency remote learning during COVID-19 crisis: Students' engagement. *Education and information technologies*, *26*(6), 7033-7055.

Khodaei, A., Feizi-Derakhshi, M. R., & Mozaffari-Tazehkand, B. (2021). A Markov chain-based feature extraction method for classification and identification of cancerous DNA sequences. *BioImpacts*, *11*(2). https://doi.org/10.34172/BI.2021.16

Kokoç, M., Akçapınar, G., & Hasnine, M. N. (2021). Unfolding Students' Online Assignment Submission Behavioral Patterns Using Temporal Learning Analytics. *Educational Technology and Society*, *24*(1).

Lam, S. F., Jimerson, S., Wong, B. P. H., Kikas, E., Shin, H., Veiga, F. H., Hatzichristou, C., Polychroni, F., Cefai, C., Negovan, V., Stanculescu, E., Yang, H., Liu, Y., Basnett, J., Duck, R., Farrell, P., Nelson, B., & Zollneritsch, J. (2014). Understanding and measuring student engagement in School: The results of an international study from 12 countries. *School Psychology Quarterly*, *29*(2). https://doi.org/10.1037/spq0000057

Lei, H., Cui, Y., & Zhou, W. (2018). Relationships between student engagement and academic achievement: A meta-analysis. *Social Behavior and Personality*, *46*(3). https://doi.org/10.2224/sbp.7054

Martin, A. J. (2007). Examining a multidimensional model of student motivation and engagement using a construct validation approach. *British Journal of Educational Psychology*, *77*(2). https://doi.org/10.1348/000709906X118036

Martin, F., & Borup, J. (2022). Online learner engagement: Conceptual definitions, research themes, and supportive practices. *Educational Psychologist*, *57*(3). https://doi.org/10.1080/00461520.2022.2089147

Mubarak, A. A., Cao, H., & Zhang, W. (2020). Prediction of students' early dropout based on their interaction logs in online learning environment. *Interactive Learning Environments*. https://doi.org/10.1080/10494820.2020.1727529

Papadopoulos, C. T., Li, J., & O'Kelly, M. E. J. (2019). A classification and review of timed Markov models of manufacturing systems. *Computers and Industrial Engineering*, *128*. https://doi.org/10.1016/j.cie.2018.12.019

Pentaraki, A., & Burkholder, G. J. (2017). Emerging Evidence Regarding the Roles of Emotional, Behavioural, and Cognitive Aspects of Student Engagement in the Online Classroom. *European Journal of Open, Distance and E-Learning*, *20*(1). https://doi.org/10.1515/eurodl-2017-0001

Perifanou, M., Economides, A. A., & Tzafilkou, K. (2022). Greek teachers' difficulties & opportunities in emergency distance teaching. *E-Learning and Digital Media*, *19*(4), 361-379.

Polyzou, A., Nikolakopoulos, A. N., & Karypis, G. (2019). Scholars walk: A Markov chain framework for course recommendation. *EDM 2019 - Proceedings of the 12th International Conference on Educational Data Mining*.

Queiroga, E. M., Batista Machado, M. F., Paragarino, V. R., Primo, T. T., & Cechinel, C. (2022). Early Prediction of At-Risk Students in Secondary Education: A Countrywide K-12 Learning Analytics Initiative in Uruguay. *Information (Switzerland)*, *13*(9). https://doi.org/10.3390/info13090401

Redmond, P., Abawi, L. A., Brown, A., Henderson, R., & Heffernan, A. (2018). An online engagement framework for higher education. *Online Learning Journal*, *22*(1). https://doi.org/10.24059/olj.v22i1.1175

Reeve, J., Cheon, S. H., & Jang, H. (2020). How and why students make academic progress: Reconceptualizing the student engagement construct to increase its explanatory power. *Contemporary Educational Psychology*, *62*. https://doi.org/10.1016/j.cedpsych.2020.101899

Riestra-González, M., Paule-Ruíz, M. del P., & Ortin, F. (2021). Massive LMS log data analysis for the early prediction of course-agnostic student performance. *Computers and Education*, *163*. https://doi.org/10.1016/j.compedu.2020.104108

Schnitzler, K., Holzberger, D., & Seidel, T. (2021). All better than being disengaged: Student engagement patterns and their relations to academic self-concept and achievement. *European Journal of Psychology of Education*, *36*(3). https://doi.org/10.1007/s10212-020-00500-6

Sedrakyan, G., Malmberg, J., Verbert, K., Järvelä, S., & Kirschner, P. A. (2020). Linking learning behavior analytics and learning science concepts: Designing a learning analytics dashboard for feedback to support learning regulation. *Computers in Human Behavior*, *107*. https://doi.org/10.1016/j.chb.2018.05.004

Skinner, E. A., Kindermann, T. A., & Furrer, C. J. (2009). A motivational perspective on engagement and disaffection: Conceptualization and assessment of children's behavioral and emotional participation in academic activities in the classroom. *Educational and Psychological Measurement*, *69*(3). https://doi.org/10.1177/0013164408323233

Sun, J. C. Y., Lin, C. T., & Chou, C. (2018). Applying learning analytics to explore the effects of motivation on online students' reading behavioral patterns. *International Review of Research in Open and Distance Learning*, *19*(2). https://doi.org/10.19173/irrodl.v19i2.2853

Tada, T., Toyoda, H., Yasuda, S., Miyake, N., Kumada, T., Kurisu, A., Ohisa, M., Akita, T., & Tanaka, J. (2019). Natural history of liver-related disease in patients with chronic hepatitis C virus infection: An analysis using a Markov chain model. *Journal of Medical Virology*, *91*(10). https://doi.org/10.1002/jmv.25533

Teugels, J. L. (2008). Markov Chains: Models, Algorithms and Applications. *Journal of the American Statistical Association*, *103*(483). https://doi.org/10.1198/jasa.2008.s254

Trichilli, Y., Boujelbène Abbes, M., & Masmoudi, A. (2020). Predicting the effect of Googling investor sentiment on Islamic stock market returns: A five-state hidden Markov model. *International Journal of Islamic and Middle Eastern Finance and Management*, *13*(2). https://doi.org/10.1108/IMEFM-07-2018-0218

Uslu, N. A., & Durak, H. Y. (2022). Understanding self-regulation, achievement emotions, and mindset of undergraduates in emergency remote teaching: a latent profile analysis. *Interactive Learning Environments*, 1-20.

Vatsalan, D., Rakotoarivelo, T., Bhaskar, R., Tyler, P., & Ladjal, D. (2022). Privacy risk quantification in education data using Markov model. *British Journal of Educational Technology*, *53*(4). https://doi.org/10.1111/bjet.13223

Vezne, R., Yildiz Durak, H., & Atman Uslu, N. (2023). Online learning in higher education: Examining the predictors of students' online engagement. *Education and information technologies*, *28*(2), 1865-1889.

Wang, H. Y., & Chih-Yuan, J. (2022). Influences of Online Synchronous VR Co-Creation on Behavioral Patterns and Motivation in Knowledge Co-Construction. *Educational Technology and Society*, *25*(2).

Wong, Z. Y., & Liem, G. A. D. (2022). Student Engagement: Current State of the Construct, Conceptual Refinement, and Future Research Directions. In *Educational Psychology Review* (Vol. 34, Issue 1). https://doi.org/10.1007/s10648-021-09628-3

Ye, Y., Grossmann, I. E., Pinto, J. M., & Ramaswamy, S. (2020). Integrated Redundancy and Storage Design Optimization for Reliable Air Separation Units Based on Markov Chain-A Game Theoretic Solution. *Industrial and Engineering Chemistry Research*, *59*(6). https://doi.org/10.1021/acs.iecr.9b04609

Yildiz Durak, H. (2019). Examining the acceptance and use of online social networks by preservice teachers within the context of unified theory of acceptance and use of technology model. *Journal of Computing in Higher Education*, *31*(1), 173-209.

Yildiz Durak, H. (2023). Examining various variables related to authentic learning self-efficacy of university students in educational online social networks: creative self-efficacy, rational experiential thinking, and cognitive flexibility. *Current Psychology*, *42*(25), 22093-22102.

Yong, K., Zaid, N. M., Wahid, N. A., Ashari, Z. M., Suhairom, N., & Said, M. M. (2021). Challenges in emergency remote teaching among Malaysian public elementary school teachers. *International Journal of Emerging Technologies in Learning (iJET)*, *16*(24), 74-90.

Yutong, X. (2021). Applications of Markov Chain in Forecast. *Journal of Physics: Conference Series*, *1848*(1). https://doi.org/10.1088/1742-6596/1848/1/012061

Zhou, J., & Bhat, S. (2021). Modeling consistency using engagement patterns in online courses. *ACM International Conference Proceeding Series*. https://doi.org/10.1145/3448139.3448161