Engagement of Students in Data Visualization for the Purpose of E-Learning Improvement

https://doi.org/10.3991/ijet.v16i02.18745

Vladimir Zotov (✉)
State University of Management, Moscow, Russia
zotovvla36@rambler.ru / ZotovVB@mail.ru

Iman Ibrahim
University of Sharjah, Sharjah, UAE

Irina Petunina
"Kuban State Agrarian University named after I.T. Trubilin", Krasnodar, Russia

Yuliya Lazareva
I.M. Sechenov First Moscow State Medical University (Sechenov University), Moscow, Russia

Abstract—The study describes an approach to e-learning based on the Moodle platform that is used to visualize participation in the learning community and is proposed to be used to inform students and teachers about their involvement in the social learning environment. The experiment involved 5 teachers and 3 experts who determined the most significant visualization indicators for the virtual learning environment dashboards. There were 42 students aged 21 to 23. The virtual learning environment is based on the Moodle and Blackboard platforms that are commonly used in universities. SocialWall allowed participants to perform actions in the social environment that are visualized in graphs under the specified criteria. A Wiki repository plugin was also added in order to accumulate student knowledge in shared structured documents stored in a shared repository. The relational database management system MySQL allows creation of additional relations, database design and administration. The visualization activities described in the study are based on modified state transition networks to analyze and visualize the student learning path. Student trajectory networks show the interaction of individual learners or groups with the course structure and material.

Keywords—E-learning; information visualization; learning analytics; social learning environment; visualization tools.

1 Introduction

E-learning and online courses in the learning environment are gradually becoming the ubiquitous components of student learning. Thus, the need for tools that monitor student participation in e-learning and measure their involvement, knowledge and skills development has dramatically increased. For example, the Russian online education market reached 45-50 billion rubles at the end of 2019 with the annual growth of 20–25% [1]. In the United Arab Emirates (UAE), 48 billion dirhams (13 billion US dollars) were allocated for the education modernization up to 2025. The program has been designed to transform the potential of professionals, introduce information and communication technologies, integrate into the global educational space [2].

It should be noted that various e-platforms have become popular in different regions of the world. Today, Moodle is the most commonly used learning management system in the world; it has over 80 million registered users in more than 230 countries [3]. The platform has also been introduced in Russian universities [4]. Universities located in the Middle Eastern and African countries, including the United Arab Emirates, rely on the Blackboard platform [5,6]. Teacher surveys showed that Blackboard 9.0 and BlackboardUltra are considered a flexible cloud environment that can easily adapt to the needs of blended learning and student support [7].

Today, during the Covid-19 pandemic, a big number of efforts have been directed towards the development of distance learning analytics dashboards to help students, educators, and other interested parties gain insight into educational behavior and learning patterns. These dashboards use visualization techniques to display various information, such as login frequency, the time taken to complete the task, click flow, and the use of tools/resources in the virtual learning environment. Initial efforts were concentrated on identifying students at risk of potential learning disabilities, but more recently, the emphasis has shifted to developing dashboards to increase self-awareness, promote positive behavioral changes, and improve academic performance [8].

Most Learning Management Systems (LMS) and web solutions are capable of recording a large amount of information about student activities, such as communication, collaboration, and participation. A number of LMS provide reports and graphs on the elementary activities of students, but they are still not very effective when it comes to student activity and involvement indicators if they are considered as separate learning process participants. Learning process improvement and support require tools and strategies that help to timely select the right information and present it in a clear and effective way [9].

Assessment of learning outcomes is one of the main issues in education. Over recent years, there has been an increasing interest in this issue due to the development of e-learning methods, and new learning models (massive open online courses) [10] require tools and measures that allow teachers to effectively and reliably evaluate large groups of students. Researchers come up with various solutions, including measures to obtain information on student interaction, didactic resources, and tools that can provide information on the student learning path [11]. The research on educational technologies is mainly focused on dashboards that allow teachers and students to customize and edit actions (lectures, quizzes, learning plan) based on quick feedback on student progress [12].

Recent studies have shown that the objectives of learning analytics dashboards are largely determined by the target audience [13]. Therefore, previously developed dashboards can be generally classified into three categories: a teacher dashboard, a student dashboard, and an administrator dashboard. Teacher dashboard usually displays student login frequency, the structure of clicks, time spent in the virtual learning environment, as well as student grades and ranks compared to others. The primary goal is to help educators identify students with behavior that may lead to poor academic performance. Student dashboards are designed to identify student learning patterns and increase self-awareness in order to encourage behavioral changes to promote academic success [14]. Administrator dashboards are designed to make strategic decisions, improve practical skills, visualize student performance, facilitate information exchange between the teacher and the student based on the learning progress, and compare the results [9].

Today the interaction in the virtual learning environment is becoming even more complicated; therefore, the number of aspects to be considered to successfully assess student performance is constantly growing. Thus, the primary objective of educational technologies is to consider all important aspects to measure the effectiveness of e-learning. This task has been successfully implemented and the e-learning system 2.0, which makes it possible to measure the key student success factor (student involvement), has already been introduced. The solution is implemented with the help of the information dashboard aimed at visualizing student participation in the virtual learning environment [15]. It has been concluded that visualization in education not only raises awareness but also has a versatile function. It has the potential to help shape the learning process and facilitate reflection on its progress, optimize academic performance by providing a visual display of data [16].

The interest in this research area and the number of approaches have been steadily growing; therefore, it was decided to consider an important e-learning environment aspect - the involvement of students in the learning process through the example of the Moodle platform used at First Moscow State University and the Blackboard platform used in University of Sharjah.

The purpose of the study is to create an opportunity to inform students and teachers about their involvement in the social learning environment through the modernization of the Moodle platform with the SocialWall plugin, the Blackboard platform with the collaborate ultra-panel that allow social communication and the dbForgeStudioforMySQL tool, which helped to develop a social learning platform allowing visualization of the actions of participants.

1.1 Visualization of student outcomes in the virtual learning environment

Analytical and prognostic models designed to describe the learning or teaching process rely on the data collected by learning management systems which capture the structure of the course and knowledge, and activity logs. These data can be supplemented by demographic data, research tools and secondary analysis of materials. The results of the analysis and modeling should be communicated to all parties concerned in order to gain a better insight into the system operation. Different parties concerned — students and teachers — play different roles in ensuring the course success, but ideally, they collaborate to exploit synergies and complementary experiences. Students should be considered equal course participants and be aware of their learning processes and the way their data will be used to continuously improve their learning resources and management system. The results of modeling and visualization must be effective, that is, the requires changes must be understood and implemented by the key parties concerned [17]. There are numerous approaches to the solution of the problem of visualizing student performance in the virtual learning environment, including the Student Achievement Measure (SAM) [18], designed to review student activities based on the time spent and methodological material used. Then, individual indicators are compared with the minimum, maximum and average values of the group. It is noted that the time spent is the key aspect of student behavior analysis. In addition, the model shows correlations between the total study time and the average time spent on a document, the number of documents used and the average time spent; it also allows detecting behavioral patterns.

The research focused on the development offers a model of "social progress visualization" or "Mastery Grids" [19] designed to engage students and direct their education through the study of educational resources. It is proposed to apply individual student progress indicators. The progress matrix measures student progress on each topic of the subject area (horizontal measurement) and the type of resources available for the topic (vertical measurement). In addition to individual visualization of progress, Mastery Grids allows comparing student performance (average indicator, students with high ranks) and emphasizes the differences between an individual user and a group. Direct comparison encourages the user to improve activities and complete various tasks.

Visual presentation of the data generated by students in the course of learning activities helps students and teachers to intuitively interpret them and quickly perceive the hidden aspects of these data, for example, student participation in the assessment in terms of the time spent and factors affecting the behavioral intention of teachers. Different forms of visual presentation are heavily used by Fine Arts and Design Colleges. To measure the expected impact of the visualizations, it is proposed to use an improved approach based on the learning analytics acceptance model (LAAM) [20]. To improve student grades in the virtual learning environment, the VeeU model was developed [11]; it includes the number of daily logins, the number and distribution of actions in the course and the completion of actions. The teacher sees daily logins as a timeline at different levels of aggregation and the student visualizes them compared to the average group indicator. A completion coefficient has also been introduced in the model; it is displayed in the calibration curve with a list of recommendations that will help the student achieve learning outcomes.

The TrAVIS model [21] collects data on communicative actions in the virtual learning environment to facilitate self-monitoring. It highlights four levels of interaction that correspond to four levels of indicators. At the aggregation level, these are the login frequency, started topics, sent messages, replied messages, and quoted messages. At the discussion level, they are views, forums, publications, reading and chatting. At the collaboration level, they include the beginning of the stream, new messages, replied messages, quoted messages, uploaded files and the level of participation. At the cooperation level, the focus is shifted from an individual perspective to the group perspective. The visualization technique at each level is a chart for each user or group that allows visual comparisons.

1.2 Visualization of student involvement in the educational process in the virtual learning environment

Learning analytics and visualization allows studying and generating reports on student involvement, performance, and learning paths in order to evaluate and optimize course design. Education is being modernized by informatization and digitalization and professional skills and knowledge, including in pedagogy, are changing rapidly. E-learning platforms and virtual learning environments are used to keep pace with technological changes and expand learning opportunities. For example, in 2017, Class Central reported that 78 million students took 9.4 thousand e-learning courses at more than 800 universities in the world [22]. Recent advances in e-learning, analytics and data mining tools allow the use of detailed data to understand and support teaching and learning [23]. It is now possible to conduct experiments in education and support efforts to achieve personalized learning goals. Learning analytics and visualization allow evaluating and comparing content modules, teaching methods, and course design in order to optimize learning outcomes and competencies based on the goals of both individual students and universities [23]. The combination of learning and visualization analytics provides new opportunities for identifying student core competencies, skills, and the ability to adapt to changes. Learning analytics (LA) is aimed at measuring, modeling and transmitting student data to understand and optimize the teaching and learning processes, as well as the socio-technical environment in which they occur. The growth of online courses and e-learning platforms (for example, edX, Udacity, Pluralsight, Udemy, Lynda) contributed to the increase of applications; learning analytics uses a variety of time, geospatial, thematic and network types of analysis and visualization [23], provides forecasts, supports authentic training.

Research on learning analytics has been conducted over the past decades; however, there is no agreed standard measurement unit to describe and identify the relationship between the course content, structure and dynamics. However, when developing a course, it is feasible to consider the LMS characteristics, in particular, the training system should support the delivery of content (reading electronic books, watching videos, taking exams) and provide access to the data on what activities each student performed at what time [17]. Modern education design and large-scale online courses have dramatically changed the mode and accessibility of learning and teaching; they also significantly influenced academic research and teaching in higher education. The growing interest in measuring student involvement in the e-learning environment contributed to the development and implementation of various dashboards; for example, VisEN [24] displays student involvement in the quick calibration table and provides additional information upon request. Students can interact with visualizations to analyze the calculation of the involvement rate, interaction with the course, study time, the volume of educational materials provided. They can compare their interactions with the total score or activity of the group.

The involvement and participation of students in e-learning have gained great importance in MOOC [25]. At the macro level, visualization is used to gain an insight into the patterns of student involvement, and the analysis shows histograms of participation and assessment disaggregated by weeks of study to confirm the overall interest; then the data are broken down to provide a detailed description of the interaction. In particular, students in MOOC can be classified into Auditors, Active and Qualified students by the type of actions performed, which is useful for a thorough analysis of the percentage and relative proportions and time evolution of interaction paths. In addition to individual participation in MOOC, social interactions have a great impact, especially when students are involved in social learning processes [26].

2 Methodology

2.1 Theoretical framework

Teachers and students should be aware of the types of interaction taking place in the virtual environment and understand how knowledge is accumulated. This is referred to as "situational awareness", which is one of the major focuses of dashboards [27]. It is believed that the quick perception of information through the toolbar is fundamental to facilitate decision-making. To achieve these goals, the following sections describe the social learning environment and the dashboard development process: from the data analysis (to determine the most suitable predictors and indicators) to the selection of the best visualization methods (to display relevant data). It should be noted that visualization methods are a powerful tool for studying learning analytics as they allow visualizing the accumulated data on student activities. In turn, visualization affects the behavior and motivation of the user (students and teachers), contributes to self-awareness and decisions to improve the approach to learning [28].

2.2 Research methodology

In the virtual learning environment, process analysis is the most commonly applied method for analyzing click logs in order to assess student commitment to given learning pathways in discrete time intervals for the interactions and transitions between views and event logs [29]. The method makes it possible to visualize three learning paths; the first path was used to highlight common paths developed for the courses that range from a simple linear path to multiple cycles with videos, quizzes, progress checks and forums. Nodes display event states in logs. The second network of paths visualizes transition patterns in each course. The final set of visualizations shows the analysis results.

It is proposed to use social learning analytics on the MOOC platform structured as network visualization in discussion forums [30]; in this case, each user is considered as a node, each response to a message is considered as a connection, and the tag cloud allows filtering connections and nodes based on the content. Tooltips help the user find a topic of interest and learn other user experience to draw conclusions about the interaction of students. Studies on the involvement in the virtual learning environment also provide [31] a visual representation of cognitive and behavioral indicators of student involvement to help teachers analyze it. To reflect the multifaceted nature of the interaction, the indicators reflect the participation of students (behavioral indicators) and the actions performed to change the structure of educational documents (cognitive indicators). Behavioral indicators are calculated based on the number of actions and time spent (the number of logins, the number of clicks on certain educational resources, the time spent on the resource, etc.). Cognitive indicators are calculated based on the actions related to the structural modification of educational documents (for example, creating, adding, updating, deleting, moving, etc.).

2.3 Research design

The virtual learning environment is considered through the customized Moodle platform used at First Moscow State Medical University and the Blackboard platform used in the University of Sharjah. The integration into the Moodle social learning environment was based on the SocialWall plugin where the Blackboard was based on the collaborate Ultra tool. The Moodle SocialWall transforms the traditional Moodle course into a social learning platform that includes message interface, message schedule, time filtering and integration with the activities and resources of the Moodle platform [32]. To implement the goals of the present study, a Wiki repository was added to accumulate knowledge to promote student cooperation. Wiki allows users to jointly create complex structured web documents and a common repository. The SocialWall plugin allows publishing posts, documents, links, and other types of resources previously shared by teachers or students. Users can post comments, share opinions and perform other actions in the social environment, which can be displayed on a graph and filtered according to the specified criteria.

Additional relations are presented through the use of MySQL - a free relational database management system, which is a database server used in various applications. The flexible MySQL management tool dbForge Studio for MySQL was used in the study; it allows automating database design and administration, entering and editing tables, creating and executing SQL scripts, triggers, and queries. The dbForgeStudioforMySQL tool is free for non-commercial use; thus, it is used in the present study as a tool for students to perform independent activities outside the classroom (Figure 1).

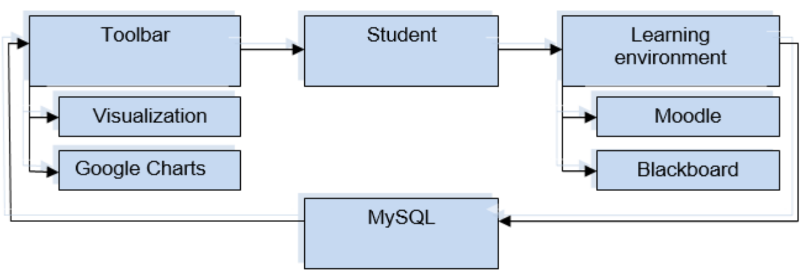

Fig. 1. Social learning environment

Note: Own development based on [33]

All user interactions that occur in the social learning environment can be tracked; they are stored in the Moodle database and in the Blackboard Collaborate Ultra tool as well. The approach is based on tracking and reveals the involvement of students in educational activities [34]. The involvement in the learning process is studied from the perspective of a multidimensional and multifaceted model, where the interactions are dependent on the context. In the context of the social learning environment, involvement is closely related to the activities performed in the learning community, as well as to user participation in various types of learning activities. First, the level of user participation in the learning community is distinguished; it ranges from low to peripheral participation. In this case, the activities include reading and limited interaction with other users. More active participation involves commenting on other users' posts, sharing knowledge resources, and contributing to community knowledge [35].

2.4 Approach to the data analysis and processing

The indicators are calculated based on the tracks accumulated in the database; the data were collected from the Moodle log tables, SocialWall log tables and the Blackboard Collaborate Ultra tool data. The indicators were collected daily followed by weekly aggregation. The system also allows monthly data aggregation. These are time comparable indicators allowing evaluation of the user interaction evolution. Next, the indicators are visualized through the Google Chars Tools API, which is a multifunctional set of tools for data visualization that creates graphs and charts. In particular, the Google Chart Tools API allows creating dynamic icons, maps, dials and displays, formulas, QR codes, as well as supplementing the functionality with one's own visualization tools [36].

2.5 Research sample

The experiment was conducted from March to April 2020. The study involved 4 teachers from First Moscow State Medical University, 1 teacher from the University of Sharjah (UAE); there were also 5 experts participating in the research: 3 experts having from 6 to 9 years of experience in teaching medical students and 2 e-learning specialists. The experts determined the most significant visualization indicators for the virtual learning environment dashboards. The users of the learning environment (students) were also involved in the experiment. It was expected that 50 people would participate in the study; the invitations were sent by email and 42 of them were accepted. Thus, 42 students participated in the study on the interaction in the virtual learning environment: there were 30 students from First Moscow State Medical University and 12 students from the University of Sharjah. The age of the participants ranges from 21 to 23 years, the majority of the participants were women (75%) and the proportion of men was 25%.

2.6 Ethical issues

Each participant allowed the collection and processing of personal data. The information on the achievements of each participant is confidential and will not be disclosed.

Students were assigned unique identifiers that were used to visualize the results of the study.

3 Results

It was decided to distinguish the following indicators of student involvement:

- Passive interactions measured by the number of likes received by the post or comment, the number of pages read in the resources shared in the community knowledge base
- Active interactions measured by the number of user posts in the community, the number of comments posted by the student in the community, the number of pages created, and the number of edits made.

At the second stage of the study, the subject of the student interest is determined. In this case, the involvement indicators are calculated on the basis of student participation in the community (interaction with other students and the teacher) and knowledge-building activities (student interaction with educational materials).

In this case, the following indicators were identified as involvement indicators:

- Social interactions of the educational process participants that are measured by the number of posts and comments, as well as the number of likes given to a message or comment
- Knowledge acquisition measured by the number of pages read in educational and methodical resources, and articles.

The first research objective is the visualization of the experimental group information in order to identify the features of student behavior in the learning environment and to reveal the level of student participation in the learning process. Further, the indicators demonstrating the position of each student on the chart are applied. The position of students is determined in accordance with the number of passive weekly interactions along the X axis and the number of active weekly interactions along the Y axis (Figures 2 and 3).

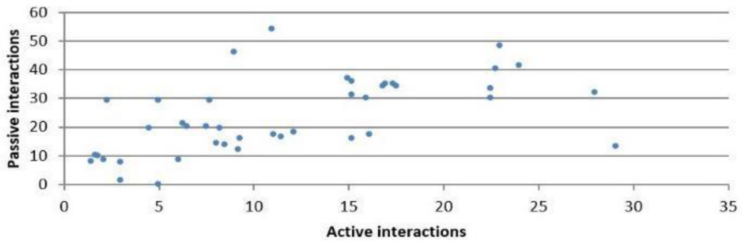

Fig. 2. Student involvement visualization: passive and active student interactions in the Moodle system

Note: Own development

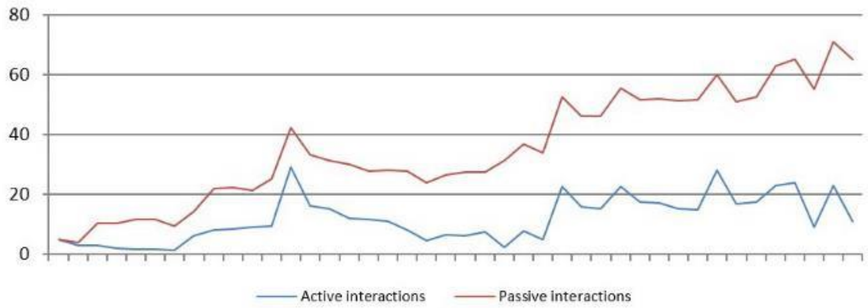

Fig. 3. Student involvement visualization based on the example of Student 11: passive and active student interactions in the Moodle system

Note: Own development

The visualization allows quick monitoring the current involvement of each student and the group through the scatter chart that displays the trend and relationships in the point cloud. When participating in the study, the students were assigned numbers to enter the system; however, in the classroom, they usually use their usernames and passwords corresponding to their first, middle, and last name. Thus, they can be easily identified. This may be necessary in order to take timely measures to correct the negative trend of student involvement in the educational process.

To analyze student behavior, it is necessary to visualize involvement tendencies; therefore, the visualization displays the details of a particular student in terms of trends and distribution. It is based on a linear time series visualization: there are two lines (one for each involvement indicator) showing involvement in passive and active interaction. As mentioned above, the indicators can be collected daily, weekly or monthly based on the analysis requirements.

The pie chart shows the distribution of the passive and active student interactions in the selected time interval, as well as the various components of the selected indicators (likes, read pages and messages, comments, created and edited pages) (Figure 4).

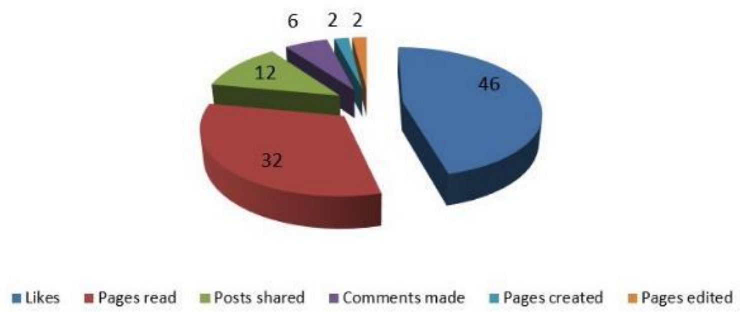

Fig. 4. Student involvement visualization based on the example of Student 11: distribution of the passive and active interactions in the Moodle system

Note: Own development

However, the analysis of the student passive or active involvement does not assess student involvement; therefore, at the next stage, the type of student involvement is analyzed. The following visualization (Figures 5-7) is a scatter plot showing the student's position by the number of weekly social interactions along the X axis and the interactions with educational resources on the Y axis. This allows the teacher to monitor the subject of interest in student interaction. After this, it is also necessary to identify socializing students and students who are involved in both social and intellectual connections.

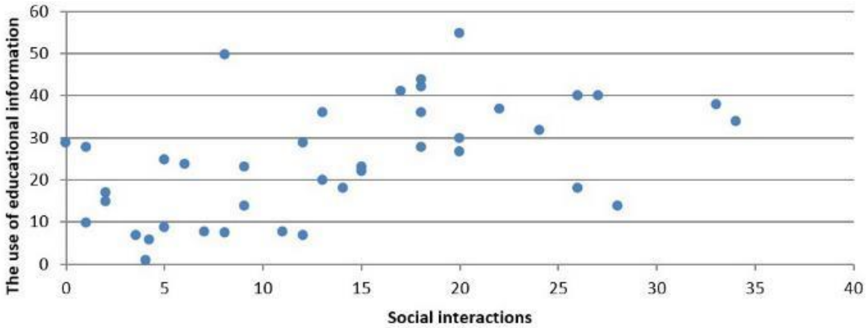

Fig. 5. Visualization of the relationship between the social interactions of students and the use of information in the Moodle course

Note: Own development

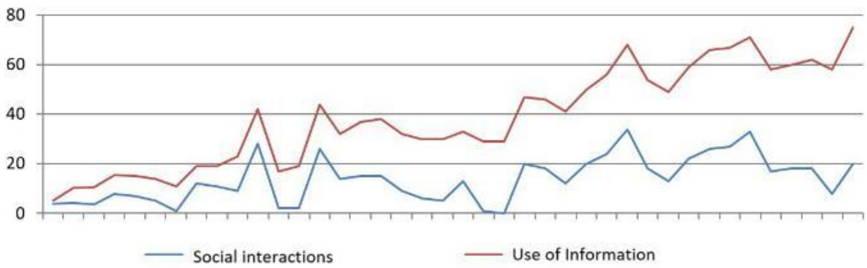

Fig. 6. Visualization of the relationship between the social interactions of students and the use of information in the Moodle course through the example of Student 11

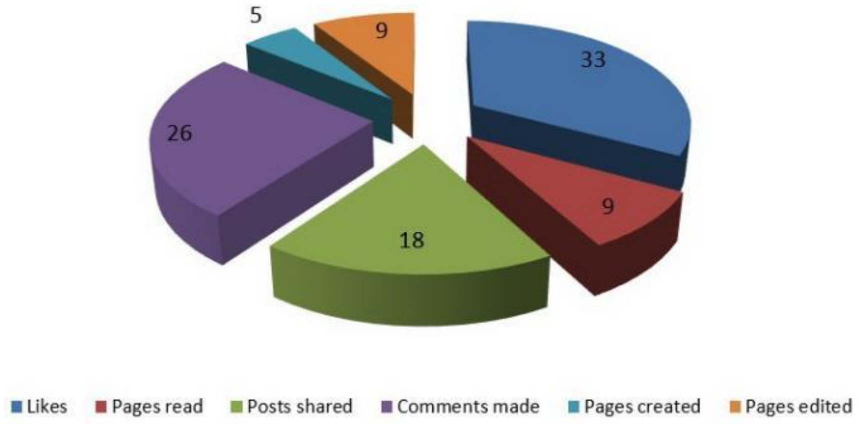

Fig. 7. Student involvement visualization based on social interactions and the use of information in the Moodle course through the example of Student 11

Note: Own development

Thus, the teacher can conclude on the active involvement of the student in commenting on posts shared by other users of the learning community (26 posts); it is obvious that the student actively participates in discussions (33 likes) and offers topics to be discussed (18 posts). However, at the same time, Student 11 does not actively study educational resources (manuals and methodological materials published in the virtual learning environment); in addition, the student does not contribute to the knowledge base in the encyclopedia developed by students in the Wiki repository. Based on the visualization, the teacher can give the student recommendations for adjusting the study plan in order to better grasp the basics of the course and get the opportunity to successfully pass the final test.

4 Discussion

Educational dashboards are widely used in various virtual learning environments, such as: learning management systems, web environment, personal learning environment, massive open online courses. Long-term monitoring of the dynamics of student involvement from the perspective of a static and dynamic approach is regarded as a promising development area. Static visualization is considered more effective for data analysis, and dynamic visualization (animated) is more effective for data perception and understanding. Animated visualization can be used for reproducing the history of events that occurred in a dynamic system of the learning environment [37]. It allows teachers and students to retrospectively track the events by going back to the beginning of the learning process, and at the same time display actions and changes while maintaining involvement by attracting attention. Nevertheless, the approach has some drawbacks; it increases cognitive load. The attention should also be given to the interaction between individual students and their groups in the learning process; it is necessary to conduct a content analysis to identify the most interesting topics and questions. In this case, interactive visualization will provide information on specific topics [38].

There was a study on creative self-efficacy (CSE) and the resources perceived by users in the sociocultural environment of the UAE confirming the applicability of e-learning tools in a unique socio-cultural context. A modified version of the Technology Acceptance Model (TAM) demonstrated that "perceived utility" and CSE are the two strongest predictors of the behavioral intent of students studying in the virtual learning environment [39].

It is also proposed to use the interactive TUT LA visualization tools, which provide an opportunity to improve learning and teaching in the context of online courses. The approach allows analyzing student activity based on automatically recorded user log data for constructing interactive visualizations. The tool has been tested in discussion forums, which are one of the major asynchronous communication means used in virtual learning environments. The TUT LA tool extends the navigation and search functions of the LMS discussion forum by analyzing the contents of the forum and automatically identifying topics for discussion. The user can expand the forum through thematic navigation and interactive search. The tools have been designed as plug-ins for the Moodle LMS [40].

It is also proposed to rely on a set of metrics and visualizations designed to reflect the key dynamic aspects of student involvement, performance and learning paths. Metrics are used to determine behavior, learning paths, interactions with the course content, actions, and grades. Visualization results show the structure of the course and patterns of student interaction with educational materials, activities, and grades. Tree visualizations are used to demonstrate hierarchical course structures and the sequence of content modules. Trajectory networks represent the paths and interactions of individual students through course modules identifying involvement models, content access strategies, and performance [17].

The visualization activities described in the study are based on modified state transition networks to analyze and visualize the student learning path. Student trajectory networks show the interaction of individual learners or groups with the course structure and material. The networks have been designed to visualize actions related to the completion of tasks (homework or exams) based on the edX clickstream data for all students in the course. In the analyzed course, activity and assessment module ego-networks demonstrate student involvement models by visualizing the transition to other course resources [17]. On the Moodle platform, it is also proposed to use a tool for studying analytics and improving the search for content and navigation to expand the capabilities of visual analytics and evaluate the relevance of the educational materials. The platform plugins allow quicker extraction of information and more efficient data tracking and management [41]. The learning process can be visually analyzed through PerformanceVis; this is a tool for analyzing and visualizing student performance in terms of time, assessment elements, as well as demographic and academic background. PerformanceVis includes four key views (overall exam grade pathway, detailed exam grade pathway, detailed exam item analysis, and overall analysis of exam and homework) that are dynamically linked to interact with the user [42].

Some learning analytics dashboards, for example SAM, are based on the CCV is tool to provide visualization of the course progress to both teachers and students [43]. It allows teachers to easily study student behavior patterns and identify the course resources that are most or least often clicked. The tool uses a higher-order network algorithm [44] to highlight critical sequences leading to different transition probabilities in order to study large-scale functions in the node-link diagram. CCVis correlates the click behavior pattern with the distribution of grades on the chart; thus, users can see what grades they will receive given a specific behavioral model. This information can motivate and encourage students to change their learning behavior into models that correlate with better grades. Visualization tools can help determine the principles of student group formation and interaction in the social learning environment. For example, NetworkSeer [45] provides information on the time, place, and causes of student interaction in the virtual learning platform forums.

To visualize student involvement on the Blackboard platform, tools to assess the activity of the online learning community (OLC) are used. OLC is a special type of social media software [46]. The teacher can track key aspects such as collaborative note-taking and advanced personal profiles of students. It is proposed to use the Elgg software as the key component of the study on student involvement primarily due to activity in micro-blogs and communities. According to researchers, the software can contribute to better learning through openness and teamwork of students, which is especially important for teaching in large classrooms where interaction between students can be minimal [47].

5 Conclusion

Traditionally, the data and reports provided by learning management systems are limited to measuring activity and performance; however, the need to monitor aspects that are difficult to understand in the process of e-learning becomes more urgent. First of all, this refers to the social interaction of students and their involvement in the learning process. Interactive visualization of student data supports student learning in the virtual learning environment, helps to monitor and evaluate academic performance and learning outcomes in order to make adjustments for improvement, both on the part of the student and the teacher. This is especially relevant in the context of e-learning, which requires students to take responsibility, self-regulation and other learning skills. Teachers can also benefit from visualization. For example, visual analysis tools can help them make decisions on pedagogical strategies, guidance, actions and interventions that can be used to support student involvement and activities. Visual analytics can also be used to get information on the way students use the course platform and study educational materials, the amount of time they spend watching videos or reading textbooks and manuals, the sequence of studying educational materials, the kind of tasks performed. This information can help teachers evaluate academic performance and identify students who are at risk of dropping out or not getting a good grade for the course. The information can be used to identify topics that students skip and educational materials that they don't use, which can help teachers improve the curriculum design and course content making it more comprehensible and interesting.

The proposed approach is an interactive process; it involves the implementation of analytics tools along with the analysis of the results. Therefore, in further studies the necessary adjustments to the previous stages of work will be made in order to provide better visual information and track trends and activity of each individual student to develop personal study plans and ensure successful completion of the course. The present study aims to satisfy the need for information that will help analyze the effectiveness of the virtual social learning environment based on student involvement indicators. As a result, it is feasible to develop and apply tools for monitoring student activity, which are of particular importance in the context of the popularity of e-learning, which allows using huge amounts of information in the learning process, but requires regular monitoring of online activities. Information visualization techniques that provide the benefits of visual perception are considered as tools for presenting data through the conversion of tracks into visual information.

The introduction and use of the dashboard when working on the Moodle platform is required in order to provide students and teachers with a tool to support the learning process and decision making on the further development of the study plan. The major advantages of the tools are as follows:

- Visual analytics helps to understand the processes that occur in the learning process
- Visualization of information contributes to activity, self-improvement, and, ultimately, the achievement of learning objectives.

The pilot study showed that the feedback provided based on the study of visual information on student involvement helps teachers develop more personalized recommendations. The present study can also contribute to the identification of the course areas which can be improved in order to facilitate data collection for the activity analysis and visualizations. In the future, additional studies aimed at measuring long-term effectiveness in the learning process will be performed. It is also planned to involve programmers in order to improve the functions of student involvement visualization tools.

6 References

[1] Kuznetsov, N. V. (2019). E-learning: key trends and barriers. E-Management, 1: 19-25.

[2] Litz, D., Scott, S. (2017). Transformational leadership in the educational system of the United Arab Emirates. Educational Management Administration & Leadership, 45(4): 566-587. https://doi.org/10.1177/1741143216636112

[3] The official site of Moodle. (2016). Moodle founder leads online learning discussion in Russia. Available at: https://moodle.com/news/moodle-founder-leads-online-learning-discussion-russia/ (assessed September 12, 2016). https://doi.org/10.5220/0005078600970106

[4] Kerimbayev, N., Kultan, J., Abdykarimova S., Akramova A. (2017). LMS Moodle: Distance international education in cooperation of higher education institutions of different countries.

Education and Information Technologies, 22: 2125–2139. https://doi.org/10.1007/s10639-016-9534-5
[5] Ahmed, H., Hassan, Z., Zawaidy, El. (2014). Using. Blackboard in Online Learning at Saudi Universities, International Interdisciplinary Journal of Education, 3(7): 141-150.
[6] Martin, F. (2008). Blackboard as the learning management system of a computer literacy course. Journal of Online Learning and Teaching, 4(2): 138-145.
[7] Aljaber, A. (2018). E-learning policy in Saudi Arabia: Challenges and successes. Research in Comparative and International Education, 13(1): 176-194. https://doi.org/10.1177/1745499918764147
[8] Kuanysheva, B. T., Aubakirova, R. Z., Pigovayeva, N. I., & Fominykh, N. I. (2019). Technologization of the Pedagogical Process as a Teacher Self-Improvement Factor. Journal of Social Studies Education Research, 10(3): 404-433.
[9] Ambarova, P. A., Zborovsky, G. E. (2019). Vocational education for people of the third age. The Education and science journal, 21(10): 59-88. (In Russian). https://doi.org/10.17853/1994-5639-2019-10-59-88
[10] Alenezi, A.M. (2020). The relationship of students' emotional intelligence and the level of their readiness for online education: A contextual study on the example of university training in Saudi Arabia. The Education and science journal, 22(4): 89-109. https://doi.org/10.17853/1994-5639-2020-4-89-109
[11] Pesare, E., Roselli, T., Rossano, V., Di Bitonto, P. (2015). Digitally enhanced assessment in virtual learning environments. Journal of Visual Languages & Computing, 31: 252-259. https://doi.org/10.1016/j.jvlc.2015.10.021
[12] Redmond, W., Macfadyen, L. (2020). A Framework to Leverage and Mature Learning Ecosystems. International Journal of Emerging Technologies in Learning, 15(5): 75-99. https://doi.org/10.3991/ijet.v15i05.11898
[13] Park, Y., Jo, I. H. (2015). Development of the learning analytics dashboard to support students' learning performance. Journal of Universal Computer Science, 21(1): 110-133.
[14] Yumashev, A. V., Utyuzh, A. S., Admakin, O. I., Doroshina, V. Y., Volchkova, I. R. (2018). Effect of mesodiencephalic stimulation on adaptation to stress and academic performance of students. International Journal of Learning and Change, 10(4): 359-367. https://doi.org/10.1504/ijlc.2018.10016003
[15] Mowla, S., Kolekar, S. (2020). Development and Integration of E-learning Services Using REST APIs. International Journal of Emerging Technologies in Learning, 15(4): 53-72.
[16] Jivet, I., Scheffel, M., Specht, M., Drachsler, H. (2018). License to evaluate: Preparing learning analytics dashboards for educational practice. In Proceedings of International Conference on Learning Analytics and Knowledge, pp. 31-40. https://doi.org/10.1145/3170358.3170421
[17] Ginda, M., Richey, M. C., Cousino, M., Börner, K. (2019). Visualizing learner engagement, performance, and trajectories to evaluate and optimize online course design. PloS one, 14(5): e0215964. https://doi.org/10.1371/journal.pone.0215964
[18] Govaerts, S., Verbert, K., Duval, E., Pardo, A. (2012). The student activity meter for awareness and self-reflection. In CHI'12 Extended Abstracts on Human Factors in Computing Systems, pp. 869-884. https://doi.org/10.1145/2212776.2212860
[19] Loboda, T. D., Guerra, J., Hosseini, R., Brusilovsky, P. (2014). Mastery grids: An open-source social educational progress visualization. In European conference on technology enhanced learning. Springer, Cham, pp. 235-248. https://doi.org/10.1007/978-3-319-11200-8_18

[20] Papamitsiou, Z., Economides, A. A. (2015). Temporal learning analytics visualizations for increasing awareness during assessment. International Journal of Educational Technology in Higher Education, 12(3): 129-147. https://doi.org/10.7238/rusc.v12i3.2519
[21] May, M., George, S., Prévôt, P. (2011). TrAVis to enhance students' self-monitoring in online learning supported by computer-mediated communication tools. Computer Information Systems and Industrial Management Applications, 3: 623-634.
[22] Shah, D. (2018). By the Numbers: MOOCS in 2017—Class Central. Class Central, Inc. https://www.class-central.com/report/mooc-stats-2017/.
[23] Perminov, E. A., Gadjiev, D. D., Abdurazakov, M. M. (2019). About relevance of fundamentalisation of mathematical training of students of the pedagogical directions during the digital era. The Education and science journal, 21(5): 86-111. (In Russian). https://doi.org/10.17853/1994-5639-2019-5-87-112
[24] Yousuf, B., Conlan, O. (2015). VisEN: Motivating learner engagement through explorable visual narratives. In Design for Teaching and Learning in a Networked World. Springer, Cham, pp. 367-380. https://doi.org/10.1007/978-3-319-24258-3_27
[25] Zhang, Y., Chen, J., Miao, D., Zhang, C. (2018). Design and analysis of an interactive MOOC teaching system based on virtual reality. International Journal of Emerging Technologies in Learning, 13(07): 111-123. https://doi.org/10.3991/ijet.v13i07.8790
[26] Di Bitonto, P., Pesare, E., Rossano, V., Roselli, T. (2015). Smart learning environments using social network, gamification and recommender system approaches in e-health contexts. In Smart education and smart e-learning. Springer, Cham, pp. 491-500. https://doi.org/10.1007/978-3-319-19875-0_44
[27] Parwati, N., Suharta, I. (2020). Effectiveness of the Implementation of Cognitive Conflict Strategy Assisted by e-Service Learning to Reduce Students' Mathematical Misconceptions. International Journal of Emerging Technologies in Learning, 15(11): 102-118. https://doi.org/10.3991/ijet.v15i11.11802
[28] Verbert, K., Govaerts, S., Duval, E., Santos, J. L., Van Assche, F., Parra, G., Klerkx, J. (2014). Learning dashboards: an overview and future research opportunities. Personal and Ubiquitous Computing, 18(6): 1499-1514. https://doi.org/10.1007/s00779-013-0751-2
[29] Davis, D., Chen, G., Hauff, C., &Houben, G. J. (2016). Gauging MOOC learners' adherence to the designed learning path.In International Conference on Educational Data Mining (EDM), pp. 54-61.
[30] Widianto, A., Purwasih, J., Perguna, L. (2020). Promoting Social Cohesion: The Development of E-Learning Management System Materials Through Life Based Learning for Sociology of Religion Course. International Journal of Emerging Technologies in Learning, 15(7): 162-170. https://doi.org/10.3991/ijet.v15i07.13339
[31] Carrillo, R., Lavoué, É., Prié, Y. (2016). Towards qualitative insights for visualizing student engagement in web-based learning environments. In Proceedings of the 25th International Conference Companion on World Wide Web, pp. 893-898. https://doi.org/10.1145/2872518.2891076
[32] Rodríguez-Rodríguez, C., Vicente-Rodríguez, R., Cortés-Moure, G., León-Pérez, C. (2019). Personalization of Moodle with the integration of most used web technologies in higher education. Iteckne, 16(1): 48-63. https://doi.org/10.15332/iteckne.v16i1.2161
[33] Raspopovic, M., Cvetanovic, S., Medan, I. Ljubojevic, D. (2017). The effects of integrating social learning environment with online learning. International Review of Research in Open and Distributed Learning, 18(1): 142-160. https://doi.org/10.19173/irrodl.v18i1.2645
[34] Siadaty, M., Gasevic, D., Hatala, M. (2016). Trace-based micro-analytic measurement of self-regulated learning processes. Journal of Learning Analytics, 3(1): 183-214. https://doi.org/10.18608/jla.2016.31.11

[35] Bhati, A., Song, I. (2019). New methods for collaborative experiential learning to provide personalised formative assessment. International Journal of Emerging Technologies in Learning, 14: 179-195. https://doi.org/10.3991/ijet.v14i07.9173
[36] Zhu, Y. (2012). Introducing google chart tools and google maps api in data visualization courses. IEEE computer graphics and applications, 32(6): 6-9. https://doi.org/10.1109/mcg.2012.114
[37] Chevalier, F., Riche, N. H., Plaisant, C., Chalbi, A., Hurter, C. (2016). Animations 25 years later: New roles and opportunities. In Proceedings of the International Working Conference on Advanced Visual Interfaces, pp. 280-287. https://doi.org/10.1145/2909132.2909255
[38] Albo, Y., Lanir, J., Bak, P., Rafaeli, S. (2016). Static vs. dynamic time mapping in radial composite indicator visualization. In Proceedings of the International Working Conference on Advanced Visual Interfaces, pp. 264-271. https://doi.org/10.1145/2909132.2909250
[39] Parkman, S., Litz, D., Gromik, N. (2018). Examining pre-service teachers' acceptance of technology-rich learning environments: A UAE case study. Education and Information Technologies, 23(3): 1253-1275. https://doi.org/10.1007/s10639-017-9665-3
[40] Tervakari, A., Kuosa, K., Koro, J., Paukkeri, J., Kailanto, M. (2014). Teachers' learning analytics tools in a social media enhanced learning environment. In 2014 International Conference on Interactive Collaborative Learning (ICL). IEEE, pp. 355-360. https://doi.org/10.1109/icl.2014.7017798
[41] Kuosa, K., Distante, D., Tervakari, A., Cerulo, L., Fernández, A., Koro, J., Kailanto, M. (2016). Interactive visualization tools to improve learning and teaching in online learning environments. International journal of distance education technologies, 14(1): 1-21. https://doi.org/10.4018/ijdet.2016010101
[42] Deng, H., Wang, X., Guo, Z., Decker, A., Duan, X., Wang, C., Ambrose, A., Abbott, K. (2019). PerformanceVis: Visual analytics of student performance data from an introductory chemistry course. Visual Informatics, 3(4): 166-176. https://doi.org/10.1016/j.visinf.2019.10.004
[43] Goulden, M. C., Gronda, E., Yang, Y., Zhang, Z., Tao, J., Wang, C., Duan, X., Ambrose, G.A., Abbott, K., Miller, P. (2019). CCVis: Visual analytics of student online learning behaviors using course clickstream data. Electronic Imaging, 1: 681-1. https://doi.org/10.2352/issn.2470-1173.2019.1.vda-681
[44] Tao, J., Xu, J., Wang, C., Chawla, N. V. (2017). HoNVis: Visualizing and exploring higher-order networks. In 2017 IEEE Pacific Visualization Symposium (PacificVis). IEEE, pp. 1-10. https://doi.org/10.1109/pacificvis.2017.8031572
[45] Wu, T., Yao, Y., Duan, Y., Fan, X., Qu, H. (2016). NetworkSeer: Visual analysis for social network in MOOCs. In 2016 IEEE Pacific Visualization Symposium (PacificVis). IEEE, pp. 194-198. https://doi.org/10.1109/pacificvis.2016.7465269
[46] Thoms, B. (2011). A Dynamic Social Feedback System to Support Learning and Social Interaction in Higher Education. IEEE Transactions on Learning Technologies 4(4): 340-352. https://doi.org/10.1109/tlt.2011.9
[47] Hill, E. (2018). The Effects of Student Activity Dashboards on Student Participation, Performance, and Persistence. Doctoral dissertation. Nova Southeastern University. Retrieved from NSUWorks, College of Engineering and Computing. (1026) https://nsuworks.nova.edu/gscis_etd/1026.

7 Authors

Zotov Vladimir Borisovich is a Doctor of Economic Sciences, Professor, Head of the Department of State and Municipal Management, State University of Management, Moscow, Russia. ZotovVB@mail.ru

Ibrahim Iman Abdelshahid − PhD, Assistant Professor at the Department of Applied Design/ Interior Design, University of Sharjah, Sharjah, UAE.

Petunina Irina Aleksandrovna is a Doctor of Technical Sciences, Professor of the Department of Higher Mathematics, Federal State Budgetary Educational Institution of Higher Education "Kuban State Agrarian University named after I.T. Trubilin", Krasnodar, Russia.

Lazareva Yuliya Borisovna − PhD, Assistant Professor of the Department of Biology and General Genetics, I.M. Sechenov First Moscow State Medical University (Sechenov University), Moscow, Russia.

Article submitted 2020-09-19. Resubmitted 2020-10-28. Final acceptance 2020-10-30. Final version published as submitted by the authors.