Premise of Learning Analytics for Educational Context: Through Concept to Practice

Yasemin GÜLBAHAR[1], Hale ILGAZ[2]

[1] Department of Informatics, Ankara University, Ankara, Turkey
[2] Distance Education Center, Ankara University, Ankara, Turkey
gulbahar@ankara.edu.tr, hilgaz@ankara.edu.tr
(Geliş/Received: 17.03.2014; Kabul/Accepted: 12.06.2014)

DOI: 10.12973/bid.2020

Abstract**—** The idea of using recorded data for evaluating the effectiveness of teaching-learning process and using the outcomes for improvement and enhancing quality lead to the emergence of the field known as "learning analytics". Based on the analysis of this data, possible predictions could be reached to make suggestions and give decisions in order to implement interventions for the improvement of the quality of the process. Hence, the concept of "learning analytics" is a promising and important field of study, with its processes and potential to advance e-learning. In this study, learning analytics are defined in two ways - business and e-learning environments. As an e-learning environment, Moodle LMS was chosen and analyzed through SAS (Statistical Analysis System) Level of Analytics. According to the analysis, some practical ideas developed. However learning analytics seem to be mostly based on quantitative data, whereas qualitative insights can also be gained through various approaches which can be used to strengthen the numerical data by providing detailed facts about a phenomenon. Thus, in addition to focusing on the learner, for research studies at the course, program, and institutional level; the research should include instructors and administrators in order to reveal the best practices of instructional design and fulfil the premise of effective teaching.

Keywords**—** learning analytics, moodle, learning analytic tools

Öğrenme Analitiklerinin Eğitsel Bağlamda İncelenmesi: Kuramdan Uygulamaya

Özet**—** Öğrenme-öğretme süreçlerinin etkililiğinin değerlendirilmesi ve kalitenin arttırılması amacıyla süreçte kaydedilen verilerin kullanılmasının inceleyen alana "öğrenme analitikleri" adı verilmektedir. Bu verilerin analizine bağlı olarak sürecin kalitesinin geliştirilebilmekte, yeni uygulamalara dair kararlar verilebilmekte ve olası tahminler ile öneriler yürütülebilmektedir. Bu nedenle "öğrenme analitikleri" kavramı e-öğrenmenin gelişimi için önemli bir çalışma alanı olarak karşımıza çıkmaktadır. Bu çalışmada öğrenme analitikleri, kurumsal ve e-öğrenme ortamları olmak üzere iki açıdan ele alınmıştır. Moodle Öğrenme Yönetim Sistemi bir e-öğrenme ortamı olarak seçilmiş ve SAS'ın ortaya koymuş olduğu Öğrenme Analitikleri Seviyeleri açısından incelenmiştir. Bu incelemeye göre uygulamaya yönelik öneriler geliştirilmiştir. Her ne kadar öğrenme analitikleri çoğunlukla nicel veriye dayalı gibi görünse de çeşitli yaklaşımlarla nitel yansımalar da elde edilerek konu hakkında daha güçlü ve detaylı bilgilere ulaşılabilir. Öğrenciye odaklanmanın yanı sıra araştırmalarda ders, program ve kurumsal düzeyde öğretici ve yöneticilere de odaklanarak öğretim tasarımı ve etkili öğretim için en ideal uygulamalara dair veriler elde edilebilir.

Anahtar Kelimeler**—**öğrenme analitikleri, moodle, öğrenme analitikleri araçları

1. LEARNING ANALYTICS AND ITS MEANING FOR SUCCESSFUL STRATEGIC MANAGEMENT

All learning processes are based on one-way or two-way communication activities, where learners interact with their instructors, other learners and content within this learning context. The evaluation of the effectiveness of this interaction is the crucial point in any learning process since it has direct effects on learning outcomes. To put it simply; for evaluation purposes, administrators and educators can access the recorded logs of the learning management systems for various kinds of data such as the number of logins, documents accessed, reports on achievement etc.

Consequently, the ideas of using recorded data for evaluating the effectiveness of teaching-learning process and using the outcomes for improvement and enhancing quality lead to the emergence of the field known as "learning analytics". Based on the analysis of this data, possible predictions could be reached to make suggestions, and give decisions in order to implement interventions for the improvement of the quality of the process. Hence, the concept of "learning analytics" is a promising and important field of study with its processes and potential to advance e-learning.

The concept of "learning analytics" is the intersection of technical and social aspects of learning processes [23]. From a technical point of view, the algorithms that form predictive systems, personalization models, semantics and network analysis require deep technical expertise. From a social point of view, these algorithms are either based on existing learning theories both individually or socially, or generate new approaches to be used for future implementations to improve quality in teaching, based on the research with mining of the relevant data. As a consequence, being an interdisciplinary area, "learning analytics" promises so much to close the gaps that exist in communication processes for online communities.

According to Elias [8], "*learning analytics is an emerging field in which sophisticated analytic tools are used to improve learning and education*" (p. 2). Moreover, the researcher mentions that this field is closely attached to some other fields like business intelligence, web analytics, academic analytics, educational data mining, and action analytics. Hence, analytics software can data mine from records to make suggestions about products, web sites and keywords depending on user actions and the context, which leads to personalized web usage. Similarly, the Society for Learning Analytics Research (SoLAR) defines learning analytics as the measurement, analysis and presentation of data for the evaluating and enhancing learning process [25].

According to Buckingham Shum and Ferguson [3] "*Learning analytics has its roots in two computing endeavors not specifically concerned with learning, but rather with strong business imperatives to understand internal organizational data, and external consumer behavior*" (p. 3). Hence, they focused on the two concepts, namely, "business intelligence" and "data mining" and investigated the phenomenon from a social perspective which they called "social learning analytics". The researchers identified social network analytics and discourse analytics under the concept "social analytics", whereas they combined content analytics, disposition and context analytics under the term "socialized analytics".

In the NMC Horizon 2012 Report Learning analytics is defined as

"*... the interpretation of a wide range of data produced by and gathered on behalf of students in order to assess academic progress, predict future performance, and spot potential issues*" (p. 22). In the report, the goal of learning analytics is also defined as to encourage and motivate educators and educational institutions to adapt educational opportunities to each learner's level of need and ability in close-to-real time [4].

Hence, from a learning point of view, where administrators, decision-makers, educators, teaching staff and learners can benefit from learning analytics, curriculum can be enhanced through the use of this data for course or program improvement, whereas learners performance can be tracked and improved through appropriate interventions based on learning goals, resources and approaches for individual purposes [15]. Moreover, for institutional improvement, data about learner profiles and performance of academicians can be used to predict useful models for learner's academic successes or failures, and together with some possible national comparisons, necessary interventions for the institution may become obvious.

At this point, it may be useful to consider the levels of analytics that can be used for different purposes. SAS (Statistical Analysis System) [22] suggest eight levels of analytics (Table-1) for answering different questions and needs. Levels start from the simplest ones and progress to the most advanced levels, and this spectrum is said to increase the degree of intelligence.

Table 1. Levels of Analytics (adopted from SAS [22])

Levels	**For Answering Questions like**
Standard Report	What happened? When did it happen?
Ad Hoc Reports	How many? How often? Where?
Query Drilldown/OLAP	Where exactly is the problem? How do I find the answers?

Levels	For Answering Questions like
Alerts	When should I react? What actions are needed now?
Statistical Analysis	Why is this happening? What opportunities am I missing?
Forecasting	What if these trends continue? How much is needed? When will it be needed?
Predictive Modelling	What will happen next? How will it affect my business?
Optimization	How do we do things better? What is the best decision for a complex problem?

The main point here is that what kind of data should be recorded, what parts should be mined for which purposes? Just to give an example, the existing tracking features of many learning and content management systems are far from satisfactory [11]. In other words, there is a large amount of data recorded in the system and often unused due to being kept in a meaningless format. If recorded data could be correlated with relevant data within or external to the system, it would be possible to generate a meaningful picture for each user about user experience, preferences and tasks. So these raw data can't be useful, it needs interpretation for using in context [14].

Moreover, McNeill [17] suggests that data is an asset for the business analytics environment, since the organizational culture is based on fact-based decisions. But he also underlines the importance of data quality. McNeil [17] defines the term *“"analytic data quality" as the methods of creating quality data from inputs, and lists the methods for addressing data quality as: “... the elimination of duplicate materials (which can artificially inflate relative weightings in analysis); resolution of terms and references (which influence how materials are classified); and entity recognition for record standardization (which provides a common benchmark to associate raw inputs)*” (p. 3).

2. MEASURING THE LEARNING SUCCESS: TECHNOLOGIES AND THEORIES

Measurement and evaluation are difficult dimensions of teaching-learning processes that directly affect the learning outcomes. If we can evaluate our teaching approaches, teaching styles, and instructional materials in terms of their being valuable to target audiences through the use of business and web analytics, then we have great potential for improvement and growth. Hence, we should be providing valuable learning content to our universities and/or companies [24].

The diffusion of interactive learning environments creates vast datasets from the use of various software like learning management systems (LMS), content management systems, intelligent tutoring systems, social media platforms and personalized learning environments, in the form of formal learning opportunities (higher education, in-service training, certification etc.) or informal ones (massive open online courses (MOOCs) etc.). Unfortunately, utilization of these huge amounts of data in favor of the components of teaching and learning processes are still very limited; such as feedback to learner and instructor about teaching methods, instructional materials, evaluation approaches, implemented learning theories, and selected technologies. This fact underlines the importance of using Learning Analytics (LA) for different purposes and considering different perspectives as a process. However, although these learning environments are commonly used in universities in developed countries, we don't have enough evidence about their effectiveness in improving learning outcomes [21].

Moreover learning analytics not only record simple variables like time or frequency of specific topics but also record more specific data likewise critical thinking, synthesis and depth of retention of concepts over time [5].

Greengard [9] defined some key components for today's business analytics solutions as: data and text mining, data visualization, forecasting, operations research and analysis, quality improvement and statistical analysis. In fact, these are the methods that we can use to grasp and monitor data for meeting the possible challenges in our learning analytics processes.

A typical Learning Analytics process is suggested by Dyckhoff, Zielke, Bültmann, Chatti and Schroeder [7]. According to researchers, the process starts with the data-gathering step (data is collected from different learners' activities including participation in collaborative exercises etc.), which is followed by *“... the mining of the pre-processed data, based on different mining techniques, such as clustering, classification, association rule mining, and social network analysis*” (p. 60). The third step is the revealing of the results of the mining process based on appropriate graphical visualizations of the analyzed data. There are many data visualization software's, which will be presented in the coming sections, for use with specific purposes. As a last step, results will help stakeholders to make any necessary interventions in their teaching-learning processes.

On the other hand, Greller and Drachsler [10] proposed a framework for learning analytics and considered six critical dimensions as; stakeholders, objective, data, instruments, external limitations and internal limitations, and they also provided sample use case and values for each dimension.

As suggested by Greller and Drachsler [10], stakeholders can be a group of learners, or tutor, moderator or even an institution, like an automated agent or commercial service provider. Objectives are mainly used for reflection or prediction purposes, like analyzing learner behaviors in terms of interactions with each other and content. 'Data' will address the related data set, which is either open or protected, that will be used for analysis in order to answer the objective, like open data set about learners' blog posts (within limited time intervals based on specified indicators like number of original posts or replies). 'Instruments' point out the related pedagogical theories and technologies which may sometimes be based on relevant algorithms for information retrieval. 'Examples' may be classifying learners based on their learning styles in order to reveal which dominant type learners are high achievers, or an analyzer algorithm to reveal the reasons for drop-outs and make predictions that could be implemented to decrease drop-out rates of learners. 'External limitations' for this framework may compose of conventions like privacy and ethics together with norms like legal use and dissemination of recorded data, whereas for 'internal limitations', acceptance and required competences like interpretation and critical thinking are considered.

Greller and Drachsler [10] suggests the use of this framework as a checklist when designing a purposeful LA process which can also be a base for designing many use cases, and underlines the importance of considering each of the six dimensions while designing. The researchers also point out challenges for LA processes as the lack of common dataset formats, a need for version control and a common reference system to distinguish and point to different datasets, methods to anonymize and pre-process data according to privacy and legal protection rights, a standardized documentation of datasets, and finally data policies (licenses) that regulate how users can use and share certain datasets.

Oliveira, McCormack and Trkman [20] analyzed the effect of the use of business analytics on supply chain performance. The researchers investigated the changing information processing needs at different supply chain process maturity levels through various statistical techniques. Their sample was composed worldwide of 788 companies from different industries. The researchers concluded that *"... the changing impact of business analytics use on performance, meaning that companies on different maturity levels should focus on different areas. The theoretical and practical implications of these findings are thoroughly discussed*" (p. 5488).

Năstase and Stoica [19] explored the relationship between analytical capabilities in planning, sourcing, making and delivering area of business performance. The researchers used business analytics and business process orientation as moderators, and considered *"... real world scenarios using reporting, data warehousing, data cubing, data mining, analysis of unstructured data, and emerging trends in cloud computing to capture real business values*" (p. 603). The researchers presented a strategy and a system for business analytics and concluded with the potential benefits of using the business analytics approach.

Generally, educators can access information to find answers to questions of what and when about learners, but interpreting this information to answer the questions of how and why is still difficult to some extent. Regarding this issue, Phillips, Maor, Cumming-Potvin, Roberts, Herrington, Preston and Moore [21] conducted a study and analyzed student access to explore student study characteristics. Realizing that a surface analysis using learning analytics was insufficient to determine about the phenomenon, they used the qualitative research approach for reaching in-depth data. The researchers also provided suggestions for developing and strengthening research about using learning analytics.

After having a diverse look at the current research conducted about learning analytics, it might be useful to provide some concrete examples for educators for possible benefits.

3. IDEAS OF EDUCATIONAL AND BUSINESS USE CASES

Instructors can benefit from information both for themselves and their students in order to make a more informed judgment. Another choice may be to intelligently process data in order to automatically predict support recommendations.

As an instructor, using a learning and/or content management system as a supplement to a traditional course or for a fully online course, one can get recorded system information about the activities of the students on a course. By this way, the instructor can understand about the engagement of students into teaching and learning activities (discussion forums, chats, web links, homework, quizzes etc.), and about the quality and quantity of students' learning experiences. By investigating the data, the instructor not only gains an insight about each learner in the class, but also has a chance to evaluate instructional resources, learning activities, learning processes and the expected outcomes and products.

As a learner, the system can identify the choice(s) of the learner in terms of his/her learning style or study habits, and provide convenient recommendations to the learner. The learner could be provided with some self-evaluation materials where some guidance towards topics that needs further study is also provided based on the achievement of the learner. Moreover, the use of semantic web or social network analysis may also provide suggestions to the learner about similar contents or the resources most preferred by his/her colleagues.

From a business point of view, in order to make the right decisions, learning analytics should be used to learn about employees' interaction with the content and peers, to learn about customers' behaviors, to learn about the most preferred content or product, and to make future predictions based on scientifically grounded approaches

Tozman [24] suggests some analytics that can be used to measure the success of a company's training as possible increases or decreases in:

- the frequency of seeing the product pages;
- the frequency of seeing the FAQ pages;
- talking about products via the internal social media;
- the frequency of seeing the performance support material provided by customer service personnel;
- the average call-handling time from internal analytics, and;
- using different media tools for accessing content.

Hence, having numerous kinds of variables, it is crucial to have a holistic view in order to achieve the desired goal of meaningful interpretations. In a parallel view, Macfadyen and Dawson [16] also revealed that, "*As the field of learning analytics continues to evolve, we must be cognizant of the necessity for ensuring that any data analysis is overlaid with informed and contextualized interpretations*" (p. 161). Either in business case or education case, one should deal with the deployment of training content, together with the context, which has an important role in accomplishing the performance expected from participants.

4. TOOLS FOR LEARNING ANALYTICS

Purdue's Signals Program, Blackboard Analytics, SNAPP, Gephi and Northern Arizona University GPS learning analytics tools have a common usage rate except for Moodle and Google Analytics.

Purdue's Signals Program was developed by Purdue University. This tool and uses the data recorded in the system about students and provides feedback to the students using different formats.

Blackboard Analytics is a tool developed by Blackboard LMS which converts the student information system data into actionable information. It provides information about usage patterns, evaluation of learning outcomes, adaptation and evaluation of online tools.

SNAPP (Social Networks Adapting Pedagogical Practice) tool is developed for the visualization of usage behavior in social networks and the analysis of discussion boards. It produces information about participants' engagement, identifying group malfunction, and student-student or student-teacher interactions.

Gephi tool is also a social network analysis and visualization tool. Gephi can produce 3D graphs about users' engagement and performances.

Northern Arizona University GPS: Academic Early Alert and Retention System tool is designed for the self-evaluation of students. It provides feedback about attendance, grades, academics and positive feedback [13].

Another important issue about learning analytics is visualization. While working on big data researchers could take advantage of visualization of data in terms of data interpretation and prediction. Some of these softwares are Wolfram, NodeXL and radar charts.

NodeXL (Network Overview, Discovery and Exploration for Excel) is a free program and especially used for exploring network graphs.

Wolfram and radar charts are also used for visualization of big data.

4.1 Example of a Tool: Google Analytics

When a user enters a web site, the software tracks mouse clicks and information requests of that user which forms web analytics. Google has software for this purpose named "Google Analytics". With the help of this analysis tool, Google Analytics, anyone has the opportunity to measure activity as it happens, defining the information that is selected for analysis, creating and analyzing organizational custom segments, analyzing specific sections of institutions/companies traffic, using dashboards, learning the path that users follow to your web site, sharing and even formatting the data as per individual preferences [26].

Moreover, with Google analytics one can see which parts of the website are performing well and which pages are most popular so that "content" will be created more easily for the future experiences of its' customers. It is also possible to measure the success of social media programs by looking at the interaction of visitors with sharing features on the site. From a mobile point of view, Google Analytics can measure the impact of mobile technology on business issues by measuring how people use mobile applications from their personal devices. Again, from a business point of view, the number of existing customers and the amount of products sold are the type of analytics that could be generated from the features available on Google Analytics. Last but not least, advertisement performance can be increased based on the data about how well the organizations social, mobile, search and display advertisements perform. Hence, the data gathered by Google Analytics can be used to determine many aspects for making future predictions and decisions about web content.

5. ANALYTICS IN HIGHER EDUCATION

In her research report, Bichsel [1] investigated the current benefits of using analytics in higher education. It was found that data is mostly used for keeping track of enrolment management, finance and budgeting, and student progress. Parallel with this use, the major perceived benefits based on predictions from the data were reported as understanding student demographics and behaviors, optimizing the use of resources, recruiting students and helping students learn more effectively. In the same report, affordability, misuse of data, regulations regarding the use of data and lack of knowledge about the use of data in making decisions are stated as concerns about the growing use of analytics in higher education. Bichsel [1] also reported as a key finding that institutions, which are more active in the process of investment, cultural change, reporting tools, expertise and infrastructure, are expected to use data to make predictions or projections in various areas.

Similarly, Brown [2] tried to offer some practical applications based on concepts. The researcher especially focused on student progress and underlined the importance of data that should be used as predictors and indicators of student progress. Brown [2] firstly mentioned dispositional factors like age, gender, ethnicity, current grade point average (GPA) and prior learning experience that exist before the course begins and offer some sign of how a student is willing to prepare for their own learning process. After that, activity and performance indicators like the number and frequency of LMS logins, the amount of time spent on the course website, the number of discussion forum messages, grades, and formative quiz scores, were mentioned by the researcher as these measures are the digital fingerprints of learners as they proceed through the learning process. Student artefacts like essays, blog and discussion forum posts, and media productions are also indicators of student performance. Hence, with all of these collected data, data mining techniques can be used to create personalized learning environments and moreover include intelligence in order to provide interventions and responses to learners to support their learning processes.

Diaz and Brown [6] also revealed how learning analytics can be helpful for instructors, for students, and for administrators. The researchers suggested some activities based on interventions to help improve student successes, such as to: implement a systematic, comprehensive counselling and intervention process; implement an integrated early-alert intervention process; develop a web-based counselling record (case) management system; and create self-help tools to connect students to resources that help them overcome challenges to their success. Thus, learning analytics are useful for supporting learner progress and providing interventions for expecting improvement in learning process.

Moreover, learning analytics can also be a supportive tool for faculty in order to help those making decisions about course activities and design, and addressing the instructional design issue in general. These kinds of decisions can be figured out by using course-based analytics. With a more holistic view, learning analytics can also influence data across an entire institution and can guide the process of forming a strategy, for planning, and for allocating resource(s).

6. EXAMPLE OF AN LMS (MOODLE): COURSE-BASED ANALYTICS

Moodle is an open source code LMS and has a very common usage rate. When Moodle usage rates were analyzed; there were found to be 87,079 registered users from Moodle sites in 239 countries [18]. Data from such a widely used LMS, is in the position for producing very valuable findings for instructors.

Log data gathered from Moodle provides insights to researchers about course activities, courses, programs and institutions. This data can be interpreted at both micro and macro levels.

In this case, Moodle has approximately 5,800 users and 200 courses on this LMS, and a micro level analysis was performed from 2 courses. Educators, researchers and also universities as an institution can increase their quality by understanding the data and making evaluations from it. Moodle gives information about the time each student spends on each course and the time spent on a particular document type. This information can be used as a guide for instructional designers and instructors alike regarding content presentations.

Moodle provides generalized data by registering users' behavior on the course base or an upper level program base as a general view. It can also produce data for each student's behavior recorded within the system. This data can contribute to studies for creating profiles of e-learning users. Moodle data provides opportunities to starters of e-learning in determining a suitable road map, and to the current users of e-learning for self-evaluation.

Within this scope, all of the log records gathered from Moodle produce information about program, course and course activities to the researchers.

Moodle analytics can produce practice data by taking the basis from the SAS report which classified the learning analytics into 8 levels. For the "Standard Report" section, researchers can use the "Reporting" menu and can access the information about course activities or personal activities via "resource view, scorm view, forum add discussion, user update etc." for each user or group. At the same time, researchers can see in which time intervals participants are active on LMS. With this data they can determine participants' studying preferences regarding time scheduling for mornings, afternoons, evenings or night courses.

Users' course following behaviors may be deduced by ad hoc analysis of data obtained from participant or group frequencies of system entrance and task performance in the system. Spatial information such as home, work, school or internet cafe use may be obtained as from these participants by inspecting the IP addresses held on the database.

Query Drilldown/OLAP level researchers can obtain meaningful data by making frequency and correlational analyses in order to find answers to the questions of "Where exactly is the problem?" and, "How do I find the answers?" Data related to points where the higher and lower successful individuals' performance differ can be produced by comparing their academic achievement and their performance in the system.

At alert level, instructors can specify the time period and the type of activities in which students' efficiencies become more concentrated by using the timing filter on the logs from Moodle. From data at this level, the researchers can answers questions such as "When should I react?" and, "What actions are needed now?".

At statistical analysis level, obtaining meaningful answers to the questions "Why is this happening?" and, "What opportunities am I missing", is possible by making analysis such as the correlation and regression between the data obtained from students' activities on the system (course following, downloading documents, joining the groups etc.), and academic achievement or different data collection tools included in the system.

At the Forecasting, Predictive Modelling and Optimization levels, answers can be obtained to a number of questions from data obtained from the 5 previous levels. For Forecasting; "What if these trends continue?", "How much is needed?", and "When will it be needed?". For Predictive Modelling; "What will happen next?" and, "How will it affect my business?". And for Optimization; "How do we do things better?" and, "What is the best decision for a complex problem?".

Analyses related to students' behavior can be made by having an efficient discussion environment on Moodle, blog, as well as usage of wikis. A commonly used analysis tool, SNAPP, makes analysis of text within forums by working with Moodle. Besides, social network analysis can be made from forums via plug-ins added to Moodle [27, 28].

Data, which can be divided into these 8 levels obtained from Moodle, show when and what kind of documents participants want to use, and these guide the instructor at the documents generating level. Data which are matched to academic achievement grades produce information which can be used to make predictions relating to the students' academic achievements. From this data, it is possible to increase the quality of learning by making arrangements related to courses or the program in the process. At the same time, this data is very important for an instructor's evaluation of the behaviors of both themselves, and the students.

Participants' usage behavior according to 2 different document types are analyzed by term as an example of data analysis from Moodle. In this regard, when graphical representations of the data are examined, it is observed that the usage of PDF type documents is higher than for videos. At the same time, concentrated usage during the March-April period can be explained as this is the exam period. But, it is an interesting finding that the ratio is not as high in May which is also an exam period.

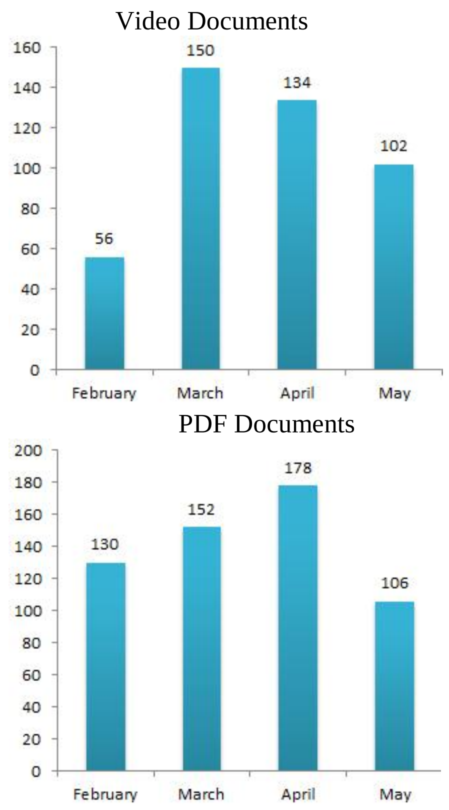

Figure 1. Participants' document usage rates

7. CONCLUSION

Learning about analytics is something new for most stakeholders in terms of thinking and learning about learning. As suggested by Buckingham Shum et. al. [3]: *"... learning analytics are designed and controlled primarily by institutional educators and administrators in order to optimise learners' performance, and hence the institution's performance. This is not at all to argue that academic/action analytics are unimportant - but it now becomes clear that this is only one of a range of possible analytics scenarios"* (p. 21).

Since all kinds of institutions and organizations are expected to deal with tighter budgets and enhancement of their service quality and quantity, making the right prediction about the future based on scientific reflections becomes more important. Organizations can make faster and more accurate decisions by analytics besides this process makes better usage of resources [12].

Learning analytics is important for bringing new insights into learning processes revealing invisible data to visible data in educational settings. This situation is highly remarkable for educational practices from the point of researchers and end users [10].

It is obvious that "learning analytics" process is based on various theoretical approaches like technologies and tools, theories and algorithms. Possible theoretical framework for effective processes should be pedagogical approaches from education era like connectivism, learning styles etc. as well as theories from other disciplines like chaos, actor network etc. On the other hand, technologies like network analysis, data mining, machine learning, semantic web, data visualization, intelligent tutoring together with statistics forms the basis for data to gain meaning by the use of the above mentioned theories.

Learning analytics have some ethical doubts on it. Some of these are about 'who is defining the measures, to what ends, what is being measured, and who has access to what data?' [3]. So the theories and technologies just stand there but decision makers have to deal with the effective solution to provide true answers to the right questions.

Hence, within such a world of possibilities and varieties, it is really difficult to choose the right approach with the right tool and to provide a meaningful result. However, based on the fact that learning analytics can be used to support not only students but also instructors, administrators and even institutions, research studies should be conducted to focus on the important points that can be enhanced through learning analytics. Some practical ideas for future research studies that can be used as answers to educational concerns:

- Instructional materials can be offered based on students' learning styles;
- Tutors teaching styles can be aligned with students' learning styles;
- Courses can be offered based on learner preferences;
- Durations for interaction can be used to define interaction patterns;
- Adaptive systems can be created;
- Self-evaluation opportunity for both students and instructors;
- Evaluation of courses and programs;
- Future institutional plans and investments based on general user profile;
- Provide insights about digital world based on real data.

As a conclusion, although learning analytics seem to be based on quantitative data mostly, qualitative insights can also be gained through various approaches which can be used to strengthen the numerical data by detailing facts about a phenomenon. Thus, in addition to focusing on the learner, for research studies at the course, program, and institution level; the research should include instructors and administrators in order to reveal the best practices of instructional design and fulfil the premise of effective teaching.

REFERENCES

[1] J. Bichsel. **Analytics in Higher Education: Benefits, Barriers, Progress, and Recommendations (Research Report)**. Louisville, CO: EDUCAUSE Center for Applied Research, 2012. Retrieved from http://net.educause.edu/ir/library/pdf/ERS1207/ers1207.pdf, 08.07.2013

[2] M. Brown. **Learning Analytics: Moving from Concept to Practice**. EDUCAUSE Learning Initiative, 2012. Retrieved from http://net.educause.edu/ir/library/pdf/ELIB1203.pdf, 12.09.2013.

[3] S. Buckingham Shum & R. Ferguson. "Social Learning Analytics", *Educational Technology & Society,* 15 (3), 3–26, 2012.

[4] L. Johnson, S. Adams & M. Cummins. **The NMC Horizon Report: 2012 Higher Education Edition**. Austin, Texas: The New Media Consortium, 2012.

[5] L. Johnson, S. Adams Becker, V. Estrada & A. Freeman. **NMC Horizon Report: 2014 Higher Education Edition**. Austin, Texas: The New Media Consortium, 2014.

[6] V. Diaz & M. Brown. **Learning Analytics: A Report on the ELI Focus Session**. EDUCAUSE Learning Initiative, 2012. Retrieved from http://net.educause.edu/ir/library/PDF/ELI3027.pdf, 7.11.2013.

[7] A. L. Dyckhoff, D. Zielke, M. Bültmann, M. A. Chatti & U. Schroeder. "Design and Implementation of a Learning Analytics Toolkit for Teachers". *Educational Technology & Society,* 15(3), 58–76, 2012.

[8] Internet: T. Elias, Learning Analytics: Definitions, Processes and Potential, http://learninganalytics.net/LearningAnalyticsDefinitionsProcessesPotential.pdf, 23.12.2013.

[9] S. Greengard. “Business Intelligence & Analytics: Optimizing Your Enterprise”. *Baseline,* 102, 18-23, 2010.

[10] W. Greller & H. Drachsler. “Translating Learning into Numbers: A Generic Framework for Learning Analytics”. *Educational Technology & Society,* 15(3), 42–57, 2012.

[11] R. Hijon & A. Velazquez. “E-learning Platforms Analysis and Development of Students Tracking Functionality”. **Proceedings of World Conference on Educational Multimedia, Hypermedia and Telecommunications,** Chesapeake, VA:AACE, 2823-2828, 2006.

[12] S. J. Jones. “Technology review: The possibilities of learning analytics to improve learner-centered decision-making”. *The Community College Enterprise,* 18(1), 89-92, 2012.

[13] Internet: C. Kennett & M. Castle. Learning Analytics: An Introduction and Critical Analysis, http://etec.ctlt.ubc.ca/510wiki/Learning_Analytics, 18.09.2013.

[14] M. L. Kent, B. J. Carr, R. A. Husted & R. A. Pop. “Learning web analytics: A tool for strategic communication”. *Public Relations Review,* 37, 536-543, 2011.

[15] P. D. Long & G. Siemens, G. **Penetrating the Fog: Analytics in Learning and Education**. EDUCAUSE Review, 46(5), 2011. Retrieved from http://net.educause.edu/ir/library/pdf/ERM1151.pdf, 10.11.2013.

[16] L. P. Macfadyen & S. Dawson. “Numbers Are Not Enough. Why e-Learning Analytics Failed to Inform an Institutional Strategic Plan”. *Educational Technology & Society,* 15(3), 149–163, 2012.

[17] F. McNeill. “Framing Unstructured Data for Business Analytics”. *KMWorld*, 1-4, 2012. Retrieved from http://www.kmworld.com/Articles/White-Paper/Article/Framing-Unstructured-Data-for-Business-Analytics-84874.aspx, 13.10.2013.

[18] Internet: Moodle Statistics, www.moodle.org, 17.09.2013.

[19] P. Năstase & D. Stoica. “A new business dimension – business analytics”. *Accounting and Management Information Systems,* 9(4), 603-618, 2010.

[20] M. P. V. Oliveira, K. McCormack & P. Trkman. “Business Analytics in Supply Chains - The Contingent Effect of Business Process Maturity”. *Expert Systems with Applications,* 39, 5488-5498, 2012.

[21] R. Phillips, D. Maor, W. Cumming-Potvin, P. Roberts, J. Herrington, G. Preston & E. Moore. “Learning analytics and study behaviour: A pilot study”. **Australasian Society for Computers in Learning in Tertiary Education Conference**, Australia, 997-1007, 4-7 December, 2011.

[22] SAS (2008). **Eight levels of analytics**. Sascom Magazine. Retrieved from http://www.sas.com/news/sascom/analytics_levels.pdf, 23.09.2013.

[23] G. Siemens & D. Gasevic, D. “Guest Editorial - Learning and Knowledge Analytics”. *Educational Technology & Society,* 15(3), 1–2, 2012.

[24] R. Tozman. “New Learning Analytics for A New Workplace”. *T+D*, 44-47, 2012.

[25] Internet: http://www.solaresearch.org/mission/about/, 08.10.2013

[26] Internet: Google Analytics, http://www.google.com/intl/en_uk/analytics/features/analysis-tools.html, 21.01.2014

[27] S. Dawson, L. Macfadyen & L. Lockyer. “Learning or performance: Predicting drivers of student motivation. Same places, different spaces”. **Australasian Society for Computers in Learning in Tertiary Education Conference**, Auckland, New Zealand, 184-193, 6-9 December, 2009.

[28] S. Dawson, L. Macfadyen, L. Lockyer, L & D. Mazzochi-Jones. “Using Social Network Metrics to Assess the Effectiveness of Broad-Based Admission Practices”. *Australasian Journal of Educational Technology*, 27(1), 16-27, 2011.