Design of Learning Analytics Tool: The Experts' Eyes View

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Abstract: Learning Analytics (LA) tools are supposed to retrieve relevant data from Learning Management Systems (LMS) and transform it into useful information for learners, trainers and education managers to increase academic achievement and effectiveness of teaching and learning. This study reveals the experts vision for LA tool features and design. The results of a survey conducted among professional pedagogues and education experts, teachers and university professors, bachelor's and PhD students are presented, with the main purpose of specifying what participants expect an LA tool to offer and how. Data analysis is discuss and visualized. The assumed categories of functionality are summarized and detailed with full list of reports each of them need to suggest for key LMS users roles: managers, teachers and students. Finally, some conclusions are drawn about the variety of users' demands and future work is outlined in order to complete the preliminary preparation before being developed an expert LA tool and the effectiveness of education being improved.

1 INTRODUCTION

Living in the era of high technology and Big Data, when mobile devices allow us to search for information and learn new things anytime, anywhere, when attractive teaching methods and training aids present curriculum, student performance statistics are still unsatisfactory (Eurostat, 2019). Moreover, one of the most common reasons for dropping out of school is "getting behind and low grades" (High School Dropout Rate, 2019). One suggestion to increase the effectiveness of education by using descriptive, predictive and prospective analysis of collected data is by using a Learning Analytics (LA) (LAK, 2011). Modern learning management systems (LMS) and their LA applications (I) improve learning outcomes (9%), (II) support learning and teaching (35%), (III) are deployed widely (9%) and (IV) are used ethically (18%) (Viberg, Hatakka, Bälter, & Mavroudi, 2018). The low spreading of LA is because their services do not always give teachers the answers they need. In addition, sometimes the pure data visualization confuses revealing of results rather than helps decision-making. This study presents the results of a survey among experts what they expect from LA functions of LMS in order data and artificial intelligence to support improvements of education. The final goal of the study is to extract requirements for building LA tool which to empower the effectiveness all players in education process through visualizing available amount of data in LMS.

2 STATE OF ARTS

There are a number of studies inquiring what LA features different LMS user's roles need. Some of them outline LA design and implementation from teachers prospective (Dyckhoff, Zielke, Bültmann, Chatti, & Schroeder, 2012), others get insights into students prospective (Kilińska, Kobbelgaard, & Ryberg, 2019) and features students really expect (Schumacher & Ifenthaler, 2018). Some researches describe smart LA (Ebner, Taraghi, Saranti, &Schön, 2015), others feature-based analysis of MOOC (Chauhan & Goel, 2017). They draw a framework of services and give useful tip for LA design by principle. In final LA tool design will also be taken into account applicable tips and tricks shared by other researchers. The study presented in this paper uses down-top technique. It starts with users' expectations and then find their place in the main framework. This approach is described in the next section.

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3 METHODOLOGY

To collect experts' opinion and analyse data the Group Concept Mapping (GCM) method (Kane & Rosas, 2017) was used. This method has been successfully applied in a number of scientific researches, for example "to identify objectively the shared understanding of a group of experts about patient handover training interventions" (Stoyanov, et al., 2012); „to identify key components used in practice when applying technologies for lifelong competence development of teachers" (Stefanova, 2013)); "to select learning outcomes and form a basis for a curriculum on handoff training for medical students" (Stoyanov, et al., 2014); "to find the way to prepare youth for tomorrow's labor market" (Kirschner & Stoyanov, 2018) and many others.

The research was conducted in the dedicated online environment of Concept Systems Inc. Global MAX (Concept System Global MAX, 2017), which provides an easy and intuitive web-based interface for organizing key activities: (1) brainstorming - generating ideas in response to a research question, (2) sorting ideas by similarity into groups, (3) rating ideas by relevance to specific criteria, and (4) analysing and visualizing data. The system allowed interface localization and work with local (Bulgarian) language which expanded the circle of experts, ready to share their experience with e-learning and in particular with LMS.

3.1 Selection of Experts

The first phase of the study ("brainstorming") involved 30 professionals from the Faculty of mathematics and informatics, the Faculty of education and the Center of Information Society Technologies of Sofia University "St. Kliment Ohridski" – pedagogues and experts in education, Science, Technology, Engineering and Mathematics teachers and university professors, PhD students and Bachelor of Science students. What they have in common is that they actively use LMS in their work or training. In the next phase ("sorting and rating") participated 20 experts. The second group completed additional questionnaire to share some social details as (1) in what role they usually use LMS, (2) how often they use LMS and (3) how many different LMS they have experience with. The results of this survey reveal that in the second phase 2 managers, 14 teachers and 4 students took participation. Half of the experts use LMS every day, 6 – at least 3 times a week, 3 – once a week and only one answered "rarely". On the terms of experience with various LMS used, 3 participants responded that they know 5 or more LMS, 2 worked with 4 LMS, 3 used 3 different LMS, 3 used 2 LMS, and 2 participators use primarily one LMS.

3.2 Data Collection

The focus question in response to which experts had to brainstorming ideas during the first stage, was "In Learning Analytics (LA) of LMS I would like to have reports for…". In order to give an idea to each expert what kind of sentences could be proposed, a sample answer was provided for each role:

- **Student:** At any point during my training, I would like to receive information about my level of coping with curriculum compared to other learners.
- **Teacher:** I would like to have summary report of students' results in other disciplines so far.
- **Manager:** I would like to see all students' grades in several courses led by a teacher.

Experts were asked to generate as many ideas as possible from the perspective of a student, teacher or manager role. In order to avoid duplication and to stimulate productivity, each participant had access to the list of already collected sentences from other participants. The brainstorming phase ended with a collection of 95 expert suggestions for LA reports, allocated respectively for student role: 23, teacher role: 45 and manager role: 27.

Before moving on to the next phase, sentences were synthesized in order to clear row data, remove duplications, or separate suggestions that describe more than one idea. Each proposal had to express exactly one idea; to be relevant to the focus question; to be clear and easy to understand; and not to be written in negative form. Kane and Trochim (Kane & Rosas, 2017) recommend the number of sentences presented for sorting not to exceed 100 in order to avoid confusions and loss of interest. After the process of idea synthesis, the number of sentences was reduced to 85 and the hint for LMS role (manager, teacher or student) was removed to avoid predefining and limiting experts to express their professional vison.

All sentences were processed outside the Global Max, imported back, and permanently shuffled to eliminate the sequence of similar ideas generated at the same time. Thus, the result of sorting was more relevant (Kane & Trochim, 2007).

During the next sorting phase, experts were free to sort all statements, according to their view of the meaning or the topic of suggestions. In special letter of invitation and in the online environment a detailed guidance on the sorting process was provided. Participants were initially asked to read all unsorted suggestions to get a holistic view, then to create the categories that describe the proposed reports, to name them as they deem fit and finally using drag-and-drop technology to put each idea into the category that best fits it. There was no limit to the number of categories required, just a recommendation that the optimal number is between 5 and 20, and not to use common names like "other", "miscellaneous", "important" or "difficult". There was a special requirement not to use the name of the LMS role like "manager", "teacher", or "student" as a category name. Each idea could be sorted into exactly one category and there should not left unsorted ideas. In case a sentence was not related to any other, the recommendation was to put it into a separate group. As a result, experts divided sentences into different number of categories between min of 4 and max of 13 with the average of 8.6.

In addition to sorting, the experts in the second group had to rank ideas on importance by two criteria: usefulness/significance and applicability/feasibility. The rating scale ranged from 1 - relatively useless/ extremely difficult to apply to 5 - extremely useful/ easily applicable.

When sorting and rating phases completed, a data check and validation was carried out to start analysis.

4 DATA ANALYSIS

The collected data were processed, rated by two criteria and their estimates were compared.

4.1 Data Processing

The collected data was processed using two statistically methods: multidimensional scaling and hierarchical cluster analysis. The results of sorting by each participant are represented by a correlation matrix called a similarity matrix, in which for each two from 85 sentences is marked 1 – if they are sorted in the same group and 0 - if are allocated in different categories. This matrix is symmetric with respect to the main diagonal. The matrices of all participants are joined into a common similarity matrix, in which the possible values are from 0 (no participant grouped the two ideas into the same category) to 20 (all experts placed the two sentences in the same category)

Using the multidimensional scaling method, this matrix is visualized as a point map in which each idea is represented as a point in a plane. The more similar are two sentences, i.e. they have a higher score in the similarity matrix, the closer to each other they are presented on the map. For this conversion, a stress index is calculated, showing the relationship between the similarities of the ideas and the calculated distance between points on the map. This index varies in the range [0-1], and the smaller is the value, the better is the correlation. The final stress index of this study is 0.2601. This value is not just "acceptable" but one of the relatively lowest according to a meta-analytic study of GCM (Rosas & Kane, 2012).

During the next phase of data analysis ideas had to be grouped into categories (clusters) by the hierarchical cluster analysis method. Initially, each idea was divided into a separate category. At each next step, the minimum distance between two clusters was calculated and their merge was suggested. Rosas and Kane (Rosas & Kane, 2012) recommend the final number of clusters to be in the range 16-5. The integrated Cluster Relay Map was used in interactive step-by-step clusters merging process.

To assist in selection of the final number of clusters a spreadsheet was also created with detailed description and highlighted changes at each step from 16 to 5. Thus, the review and evaluation of data led to conclusion that the best number of categories with reports for this research is eight. The further step of merging would have joined reports about course feedback and LMS usage. The first one involved evaluation of teaching methods and course content whereas the second one takes into account the activity of all students in LMS.

The clusters' names at each steps varied, following the titles experts gave during the creation. In final version, these names ware modified manually in order to clearly describe the reports they group. Figure 1 shows the final list of clusters with their names, abbreviations and number of sentences in each one.

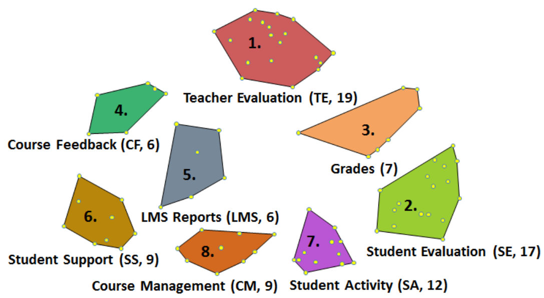

Figure 1: Final clusters distribution.

An indicator of how typical each idea is for the cluster it belongs is a parameter bridging value. It varies in interval [0, 1], with lower values indicating that the idea is typical for the cluster, while higher values indicate that the location of the idea is at the "boundary" of the cluster, i.e. if the number of the final groups was larger, it would most likely be part of another group.

Among the experts' ideas there was a suggested report with bridging value = 0 (To visualize a summary report of teacher's feedbacks for different years; category Teacher evaluation) as well as a report with bridging value = 1 (In case of overdue activities by a teacher, the system to send a notification, category Student support). In view of the recommendation if a sentence is not associated with any other, to put it into a separate group, such idea is expected to have a higher bridging value.

An average bridging value can also be calculated for each of the 8 categories with reports. The smaller the value, the more unanimously experts consider ideas in the cluster should be grouped together. Conversely, the higher the bridging value of a cluster, the more general it is with respect to its reports. Table 1 shows the average values of the categories, sorted in ascending order. It could be seen that values range from 0.21 to 0.67, with the lowest in the Teacher evaluation and Student activity categories and the highest in Course Feedback cluster.

Table 1: Clusters descriptive statistics.

Category abbreviation	Standard Deviation	Median	Average
TE	0.05	0.27	0.21
SE	0.05	0.27	0.26
Grades	0.05	0.44	0.43
CF	0.16	0.61	0.67
LMS reports	0.05	0.53	0.51
SS	0.10	0.47	0.50
SA	0.05	0.21	0.21
CM	0.06	0.38	0.37

In addition to sorting, experts rated all the proposed reports on two criteria: usefulness/relevance and applicability/feasibility on a scale of 1 (relatively useless/extremely difficult to apply) to 5 (extremely useful/easily applicable).

4.2 Rating Ideas by Usefulness

The range of average scores by criterion usefulness/significance is from 3.10 to 4.60. Two suggestions received the lowest rating: (1) During a course to be visualized in percentage what part has already passed and what part remains (M=3.10; SD=1.3) and (2) To be visualized statistics on teacher's activity in forums (M=3.10; SD=0.8). As the most useful is esteemed one suggestion: In teacher' view to have a graphical representation of schedule conflict (for tests, home works, and exams) between current course and the other courses for the same students (M=4.6; SD=0.7).

Further data analysis by category revealed both a difference in the ranges of assessments and an opinion on the corresponding ideas. For example, managers set min score of 2.5 on 4 suggestions and max of 5.00 on 10 ideas; teachers assessed 1 idea with min rate of 2.86 and one with max of 4.75; and students respectively one proposal with min of 2.50 and one of max 4.75. Moreover, there is no cross-section of either the minimum or maximum average rating of an idea for report by the three expert groups.

Another interesting dependency can be seen in usefulness rating according to the experience of the experts in using different LMS. The higher the proficiency of the evaluators, the wider the range they put in grades, and the greater the number of ideas evaluated as being the most useful. Most experienced experts (know 5 different LMS) have given estimates in the range [2.00-5.00], and the experts working with single LMS [3.00-4.89].

From estimates of the individual ideas, an average score for each category of usefulness/significance can be calculated. Figure 2 shows that as the most useful is evaluated the category Course feedback with score 4.26 out of 5.00 and as the least useful - the categories Student evaluation and Student activity with score 3.81 out of 5.00.

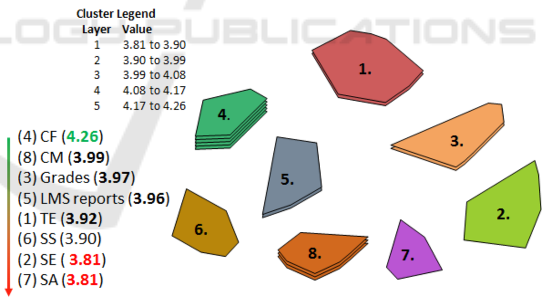

Figure 2: Clusters rating by usefulness.

The results of these evaluations will be used to select and prioritize the reports that the planned LA tool should offer.

4.3 Rating Ideas by Applicability

The average score of ideas given by experts on the second criterion applicability/feasibility vary in the range [2.95-4.45]. As the most difficult to perform is marked: To visualize an estimated time for publishing results of a test/homework/exam (M=2.95; SD=1.23) and as the easiest to implement is ticked: For each assignment/activity to be visualized a list of all students already submitted it (M=4.45; SD=1.05).

Further analysis shows that managers have given a max score of 27 ideas, while the other two roles are unanimous for the best applicability of one and the same suggestion: For each assignment/activity to be visualized a list of all students already submitted it. Managers and students find it difficult to implement the report mentioned above as the lowest applicable, while teachers are sceptical about the idea: Generating recommendation for grouping students together for teamwork on a common task with a common assessment.

Data analysis from position of experience with more different LMS shows that the experts with more experience assessed more critically. They put a lower min score than other participants and evaluated the feasibility of the suggested reports in a wider range.

From estimates of the individual ideas, the average rating could also be calculated for each category. Figure 3 shows that the most feasible are reports in the category Grades with score 4.16 out of 5.00 and the most difficult to implement – in the category Student support with score 3.73 out of 5.00. Concerning groups, the difference between the min and max average scores is not very high.

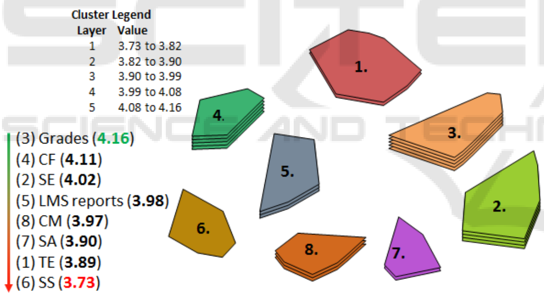

Figure 3: Categories rating by feasibility criterion.

The results of these evaluations will also be used for selection and prioritization of the reports that the system under development should offer.

4.4 Comparison of Scores on Both Criteria

The comparison of average scores on both criteria for the 8 categories is also interesting. Some of clusters received almost the same rating, for example LMS reports (usefulness: 3.96, feasibility: 3.98) and Course management (usefulness: 3.99, feasibility: 3.97). Others are rated as much more easily to apply then useful, such as Grades (usefulness: 3.97, feasibility: 4.16) or Student evaluation (usefulness: 3.83, feasibility: 4.02), or more useful then applicable, such as Student support (usefulness: 3.90, feasibility: 3.73). Overall, the usefulness is evaluated higher than the feasibility (Figure 4).

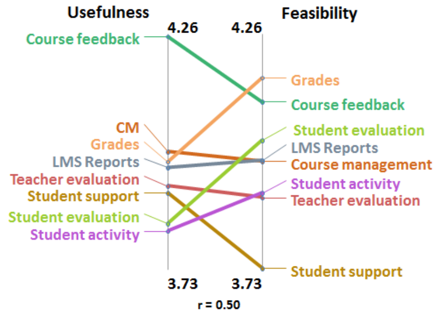

Figure 4: Categories rating comparison.

Further data analysis reveals differences and trends in rating of categories by different groups of experts. For example, we can compare estimates given by participants according to their LMS' role. By both criteria, managers' ratings vary over a wider range (3.29-4.43; 3.44-4.93) than teacher' (3.90-4.29; 3.71- 4.05) and students' ratings (3.54-4.19; 3.71-4.80) (Figure 5). For managers, the most useful reports concern the results and students' success; teachers consider the most important feedback that trainees give to their course and students place first supporting learners.

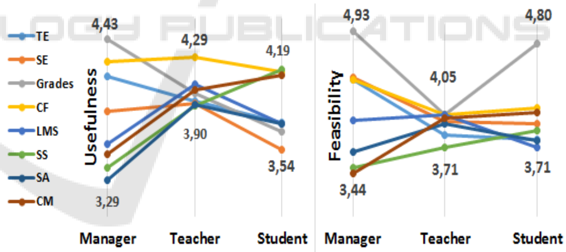

Figure 5: Category usefulness by experts' role.

On the feasibility criterion all experts put first learning outcomes, and the most difficult to implement is Course management according to managers (3.44), Student support according to teachers (3.71), and Teacher evaluation according to students (3.71) (Figure 8).

Rating based on experts' experience with different number of LMS indicates that knowing more systems allows grading of the usefulness and feasibility in a wider range, while experience with a single system limits estimates in a narrow range. From the estimates of experts, experienced less LMS another interesting dependency can be seen: the more useful they find a report, the less applicable it is (Figure 6 and Figure 7)

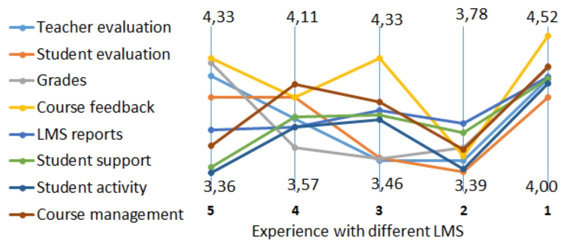

Figure 6: Clusters usefulness by experts' experience.

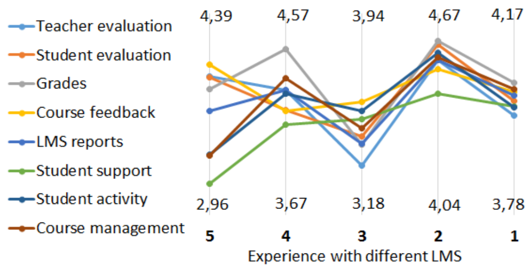

Figure 7: Clusters feasibility by experts' experience.

The rating by frequency of using LMS by participants indicates that experts who use such systems every day have estimated the categories in a narrower range, with closer values, while the experts who use LMS less frequently in their work have put grades more widely, reaching the maximum of 5.00 (Figure 8 and Figure 9).

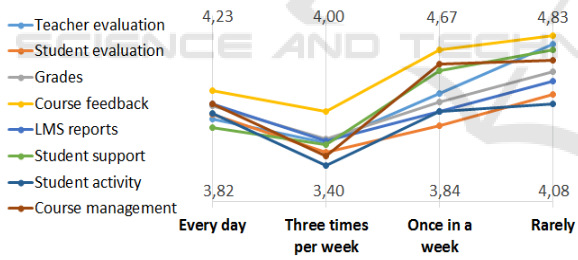

Figure 8: Clusters usefulness by experts' LMS usage.

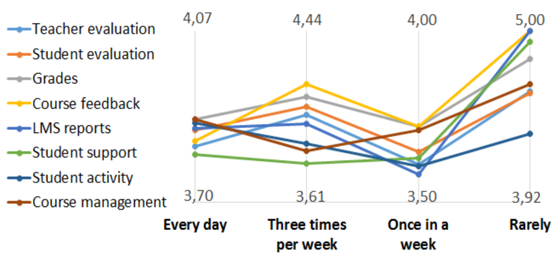

Figure 9: Clusters feasibility by experts' LMS usage.

Data analysis is summarized in the next section detailing the list of reports that experts defined and ordered to be presented in each LA category of LMS for each system user's role.

5 RESULTS

The results from data analysis can be summarized in scatter-plot "go-zone" diagrams dividing the area into four zones according to the average values calculated by the ratings on both criteria: usefulness/significance and applicability/feasibility (Figure 10).

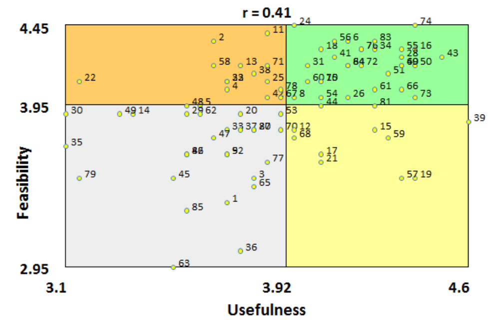

Figure 10: Go-zone diagram of ratings in all categories.

In the upper-right "green" zone, or the area of quadrant I in the plane, are visualized ideas that got scores above the average on both criteria; in the area of quadrant III, or the "grey" zone, are placed the suggestions evaluated below the average on both criteria; and in the quadrants II and IV are allocated reports estimated above the average by one criterion and below the average by the other one.

The following relationships were searched for in each category:

- How many and which reports experts from each role are put into the green zone;
- How many and which are the unique reports placed in the green zone as very important by experts in any LMS role;
- How many and which are the unique reports that participants by each LMS role unanimously appreciated above the average on both criteria;
- Are there reports put in the grey area by experts in all LMS roles at the same time;
- Are there reports rated by experts in one role as very important but below the average on both criterion by experts in another role;
- Are there reports evaluated by all experts above the average on one criterion but below the average on the other criterion.

In the first version of the tool all proposals, which experts rated above the average will be implemented. The reports assessed above the average on one criterion only will be revised and implemented in next iteration. The grey zone ideas will be further revised.

Table 2 shows the distribution of reports in the category Teacher evaluation. As the most useful and applicable, the experts in the role of managers evaluated 9 reports, the experts in the role of teachers – 10, and the experts in the role of student – 6.

Table 2: Number of suggestions in Teacher evaluation.

Manager				Teacher				Student			
I	II	III	IV	I	II	III	IV	I	II	III	IV
9	2	7	1	11	3	5	1	6	3	5	5

Totally 11 unique ideas, 5 of which are estimated as the most useful by all experts will be implemented.

In Student evaluation category (Table 3), there are 9 suggestions in the green zone for managers, 4 - for teachers, and 5 - for students. Totally 12 unique reports without crossing the most important and the least important according to the three roles of experts. 4 reports from the managers' view and 2 from the teachers' one will not be displayed in LA section for students. The same time one of the student's report will not be displayed for managers.

Table 3: Number of suggestions in Student evaluation.

Manager				Teacher				Student			
I	II	III	IV	I	II	III	IV	I	II	III	IV
9	4	2	2	4	5	3	5	5	5	6	1

In this category 12 reports will be implemented.

In Grades category (Table 4), there are 4 highly important suggestions according to managers, 3 for teachers, and 3 for students.

Table 4: Number of suggestions in Grades.

Manager				Teacher				Student			
I	II	III	IV	I	II	III	IV	I	II	III	IV
4	2	0	1	3	0	4	0	3	1	2	1

Totally 6 unique reports, with no sections between the most and the less important according to experts of all roles will be implemented. One of the manager's report will not be displayed for teachers and students because they put it into the grey zone.

The Course feedback category consists of 3 suggestions in the green zone for the managers, 3 - for the teachers, and one - for the students (Table 5)

Table 5: Number of suggestions in Course feedback.

Manager				Teacher				Student			
I	II	III	IV	I	II	III	IV	I	II	III	IV
3	1	2	0	3	2	1	0	1	2	1	2

In total 5 unique reports will be developed and visualized in LA section for this category, one of them will not be offered in current form to managers. One suggestion is marked as least important from all roles of experts.

In LMS reports category (Table 6), there are 2 highly important suggestions according to managers, 1 for teachers, and 1 for students, or 3 unique suggestions without any sections between different role's votes will be implemented.

Table 6: Number of suggestions in LMS reports.

Manager				Teacher				Student			
I	II	III	IV	I	II	III	IV	I	II	III	IV
2	1	3	0	1	2	0	3	1	2	1	2

The Student support category includes 3 suggestions in the green zone for the managers, 2 - for the teachers, and 4 - for the students (Table 7). Totally 6 unique reports will be implemented, one of which will not be displayed in manager's view.

Table 7: Number of suggestions in Student support.

Manager				Teacher				Student			
I	II	III	IV	I	II	III	IV	I	II	III	IV
3	1	3	2	2	3	3	1	4	2	1	2

In Student activity category (Table 8), there are 4 highly important ideas according to managers, 5 for teachers, and 5 for students. Totally 9 unique reports will be implemented, 2 of which not be included in manager's view, 2 – in teacher's, 2 – in student's. One proposal is evaluated as more useful than applicable

Table 8: Number of suggestions in Student activity.

Manager				Teacher				Student			
I	II	III	IV	I	II	III	IV	I	II	III	IV
4	2	3	3	5	1	4	2	5	1	4	2

The last category Course management includes 3 suggestions in the green zone for the managers, 4 - for the teachers, and 4 - for the students (Table 9).

Table 9: Number of ideas in Course management.

Manager				Teacher				Student			
I	II	III	IV	I	II	III	IV	I	II	III	IV
3	2	3	1	4	2	2	1	4	0	3	2

Totally 7 LA reports will be developed in this section, one of which will not be displayed for managers, one – for teachers, and 2 for students.

Totally 59 reports will be provided and visualized in the LA part of LMS meeting the user requirements of the three main system roles.

6 CONCLUSIONS

The presented study summarizes the most valuable, according to the education experts (including students), LA features expected to be available in the LMS, based on collected big amount of data and artificial intelligence. Results show that the experts in the most popular LMS systems and their LA features have higher demands and expectations. Even for the reports that are available in these systems, experts suggest variants and details for missing cases. In addition to formulating the most LA services of a modern LMS, the result list was further subjected to design thinking activity. By critical evaluation and filtering common existing reports, brand new needs and requirements were extracted.

Before implementation of the LA tool to be done, one more study is plan, investigating what types of visualization of reports experts (three already defined roles) would like to be available as LA means in LMS. Data visualization methods for these reports will be proposed and experts will be asked for their professional opinion on which visualizations carry the most useful and practical information at a glance. Both group of results – from the presented and from next study will be used for implementation of LA tools in LMS, supporting via data and ICT effectiveness of all participants in education process.

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