Analytics Prototype for Data Driven Decision Making for Blended Learning Strategies in HEI

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Abstract: In this paper we present a tool that introduces data-driven decision making concerning the implementation and adoption of blended learning in higher education. We identified key groups from the university's administration that are directly involved in the learning and teaching processes and captured their goals and perspectives in the context of eLearning processes. We used these perspectives and goals to sketch out systematical introduction of data-driven decision making processes which can create sustainable impact on their work and the blended learning scenarios. This resulted in building a web-based prototype that visualizes usage statistics and analytics of the log data extracted from the university-wide learning platform. This prototype contains indicators and visualizations mapped to the goals and perspectives of the identified key user groups, in order to provide insight how the different faculties teach and learn utilizing the platform and provides actionable intelligence to better distribute resources and support the staff and students in their respective blended learning scenarios.

Keywords: Decision Making, Analytics, Learning Data, blended learning strategy

1 Introduction

Evidence based, or data based decision making is the process of analyzing and evaluating data to improve learning offerings and resources, curriculum, and make informed decisions about the teaching and learning processes [Cr06] [Ho12]. These institutional decisions are too important and critical to be based on intuitions, or presumptions. These decisions require facts, knowledge, and analytics. In theory, visual analytics and data analytics should be the main sources of information in decision making, representing an improvement over intuition. Unfortunately, in practice, this is not the case. Often, decision making is usually based on intuition, presumption, and on accumulated experience, without any specific data or analysis [CDO07]. Since, most universities and higher education institutions (HEI) in Germany are public institutions, which means there is a certain level of transparency and accountability to the public not only of the decisions, but also of the decision-making process. Hence, such position affords the higher education institutions to evaluate, revise, and improve the tools they use for decision making.

When it comes to institutional decisions and decision-making in higher education institutions concerning the learning and teaching processes, there are two main groups of stakeholders: students and faculty, and administrative bodies. In the second group, there

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are students and faculty members that belong to different administrative bodies, but in this case, they have different roles[Ch12]. The ongoing work presented in this paper focuses on the administration stakeholder group. This group includes the blended learning coordinators² (one for each faculty), the committee for eLearning (consisting of all BL coordinators, plus the management leadership from the institutes responsible for eLearning processes and implementation), the rectorate and dean(s) responsible for teaching, academic affairs, planning, development, control and institutional research, and the center for teaching and learning (including the developers' team). Each of these users (or user groups) has different responsibilities, perspectives, and goals concerning their eLearning process and scenarios. In the following section, we will outline the salient points of the goals and perspectives of the different people within the administration. This work is part of an ongoing project at RWTH Aachen University, called AIX – Future teaching & learning funded by Stifterverband which aims to provide the HEI administration possibilities to examine, classify and evaluate their investment and efforts in fostering blended learning concepts and implementations.

2 Goals and Expectations

In the previous section, we presented several user groups who are directly involved in the eLearning processes and infrastructure at RWTH Aachen university. The goals and perspectives from the different user groups were collected in two phases. In the first phase, we conducted a literature review and several brainstorming sessions to identify and sketch out the different perspectives of the different user groups. The second phase were a series of semi-structured interviews with different people from the identified users' groups to gain an insight about how they collect and gather pieces of information, and how they use this information in their decision-making process. The intermediate results from the first phase were used as a basis for guidance of the semi-structured interviews in the second phase. The different involved groups and the salient points of their respective goals and perspectives are summarized in Table 1.

It is noteworthy to mention that different groups responsible for different aspects of the eLearning processes have similar, or even common goals, but still have different perspectives. For example, the developers' team is interested to learn how different faculties use the various functionalities of the learning platform in their course rooms and how (when, how much, which devices) the users interact with the different modules in these courses. This way they can evaluate their modules, identify patterns of usage, potential problems, system load, and other parameters that could help improve the platform from a developer's/technical point of view. At the same time, the blended learning coordinators, who are responsible for implementation of the blended learning initiative would like to know the same thing, but from a different perspective. They also

² Blended Learning Coordinators are responsible for implementing the blended learning initiative at RWTH Aachen University. They are part of a rectorate appointed committee whose goal is to oversee the university-wide implementation of blended learning concepts.

need this information, how different users from different faculties use the learning platform; on which modules, they use to implement their teaching and learning approach; does their approach relies on lecture scripts, or also includes videos and media; whether collaboration and discussion is useful; is formative assessment integral part of their courses; and many questions that follow under implementation of different eLearning approaches and strategies.

Another example is that the members of the department for planning, development, and control is interested in how different faculties use the underlying learning and technical infrastructure. They need to have and overview and compare how different faculties implement their eLearning initiative(s), which also coincides with the perspective of the coordinators, who need to oversee and analyze that on individual faculties to come to different conclusions and decide upon different actions and measures.

User group(s)	Goals and Perspectives
Developers Team IT Staff Platform Support and Qualification Team	 Learning Platform Usage Patterns Concurrent users and requests (traffic) Different modules use frequency OS/Devices distribution among users Errors and Bugs identification
(Blended Learning) eLearning Committee Blended Learning Coordinators	 Resources planning Implementation of different eLearning approaches Feedback and guidance for faculty and students Continuous Learning vs. Cramming Success rate/Evaluation of Blended Learning initiative Scientific literature/library resources use
Rectorate Department for planning, development, and control	 Accountability and University Image Resource Allocation Effective use of learning resources and infrastructure among different faculties

Table 1. Users involved in decision making with their respective goals and perspectives

Another aspect that was revealed to us during the interviews was that to gather and aggregate information about how to analyze and decide over, is the lack of tools and lack of readily-available and understandable data, which can support them during their work. They do have different data available from them through different channels (mostly qualitative) such as: number of (new) students, students evaluating teaching, log data, interviews, and surveys, but nothing conclusive nor systematic on a regular basis. Furthermore, they must invest a lot of time and resources just to understand the data, because it comes in a variety of forms, factors, and amount, and thus requires a versatile

skill set which goes beyond the scope of their work. This makes it very challenging to analyze and assess the eLearning scenarios and situations just to get an overview of the situation, and nearly impossible to make informed decisions and undertake measurements to achieve their respective goals regarding the eLearning initiatives and activities at RWTH Aachen University.

3 Project

In the previous sections, we presented the basis why the administration needs an analytics tool to support them in achieving their goals in the context of eLearning. According to [Ko08], in order to systematically introduce evidence based or (data-driven) decision making, there is a four-phase process that can help in creating sustainable impact on the learning/teaching processes. The four phases are: data collection, data connection (connecting the data), working with the data, and findings confirmation. We followed this process methodology when we worked on the AiX Analytics prototype. The prototype itself is a web-based prototype that visualizes the usage statistics and analytics of the log data from the learning platform at RWTH Aachen University. The prototype consists of three main building blocks: data analysis and management, RESTful application engine, and User Interface. The building blocks correspond with the first three parts of the process methodology.

3.1 Data Management and Analysis

The primary data source of our prototype is the anonymized log data generated from the learning platform L²P used at RWTH Aachen University. We receive the anonymized version of the log data from the servers that run the learning platform on regular basis for the past year. The data itself contains the timestamp, hashed IP address of the request, the client agent, the processing time, the request/response size, the URI of each request, and the response code. The platform logs that we receive are raw and unfiltered. This means that before we start the analysis, we need to clean up the data and prepare it for analysis. After this step, the analyzers extract and aggregate the information, and save the derived data and useful information. The raw data is kept for 15 days and deleted (data privacy conformant).

3.2 Data Connection

We built a RESTful application engine to connect the derived and analytics data with the user interface. The RESTful application engine is a Web API application consisting of different web services methods (HTTP services) that provide data and analytics to the user interface. The HTTP methods deliver the requested results in JSON format. The application engine itself is modular and already has wide range of methods, and, if necessary, it is straightforward to extend it with new methods.

3.3 Working with Data (User Interface)

The user interface provides a set of visualizations that presents the learning data in various forms interactively for the different users' scenarios and goals. The main emphasis of the visualizations in the prototype is easy-to-understand visualizations, which the stakeholders can use to support and enhance their day to day activities, which can in turn help in achieving their respective goals. We split the interface into two main aspects. The first aspect covers the platform itself and the different modules that exist in each course room. The second aspect covers individual faculty's overall activities divided per semester and summarized over the entire timespan of the available data. The visualizations are interactive (filtering and zoom-in functionality) and enable the user to focus on specific parts of the visualization. The reason behind this split can be inferred from the goals and perspectives of the different stakeholders. Although the users have similar, or overlapping goals, they have different perspectives. We used knowledge and guidelines for implementation of analytics tools and prototypes, which we have already gathered from previous experiences and research. In [Dy14] is provided a requirements catalogue which depicts in details what one needs to consider when building analytics prototypes and tools. We selected a subset of these requirements and guidelines according to the questions we need to answer, the data analytics literacy of our user groups, and the types of visualizations we needed to develop. The visualizations in the prototype are simple and responsive, thus the cognitive effort upon the user is low, and she can concentrate on the visualizations themselves, instead of concentrating on understanding the interface. Furthermore, the visualizations themselves are interactive (filtering and zoom-in functionality) which enables the user to focus on specific parts of the visualization and drill-down into the data to get deeper understanding about the data. The interactions with the visualizations are always coupled with informative tooltips (bound to mouse-hover events) to provide feedback about what is displayed at a given time and place [Dy14]. We developed around 30 different indicators, which try to answer the questions and goals we extracted in our phase. For the visualizations themselves, we use the Highcharts³, interactive JavaScript chart library. In the next section we will display three scenarios /usecases which show the tool's potential, and also provide interesting insights about how different faculties and field of study implement the blended learning scenarios in HEI.

4 Use Cases and Insights

The first scenario is to see how different faculties use the assessment functionalities on the learning platform. This scenario is useful for the blended learning coordinators and the developers' team. The coordinators can gain an overview of how the different faculties implement formative assessment in their eLearning scenarios. The developers' team can identify different usage patterns of the assessment features on the platform in order to provide more streamlined learning and teaching experience. Figure 1 shows the usage over

³ http://www.highcharts.com/

one year of the assessment modules available on the learning platform (Assignments, eTests, Gradebook, and Exam Results).

As one can see that during the semesters (from April till July 2016, and October 2016 till February 2017) the largest and continuous usage of different assessment modules comes



Figure 1 Assessment Distribution among the faculties

from the Faculty of Mathematics, Informatics, and Natural Sciences (Faculty 1). In the exam phases, the usage of assessment modules increases because other faculties publish the results of the exams. From this one can conclude that Faculty 1 uses the assessment modules from the learning platform for formative assessment as an integral part of their blended learning strategies. The other faculties (for example Civil Engineering, Geology) are lagging behind. This can be seen from Figure 2. Figure 2 shows the usage of assignments' module at the Faculty of Mathematics, Informatics, and Natural Sciences, and usage of assignments at the Faculty of Civil Engineering. One can clearly identify the weekly peaks on the left which correspond to weekly assignments, while on the right there



Figure 2 Assignments on Faculty of Natural Sciences vs. Civil Engineering are only peaks for two weeks in January.

The second scenario involves usage of different media in the learning processes and scenarios at the different faculties. If we look at the overall media use, distributed among the faculties, half of the usage comes from the Faculty of Mechanical Engineering (Figure 3). This visualization is intended for the eLearning committee and the department for planning, development, and control. These stakeholders can get an overview which faculties implement video-based learning, and how it is distributed among the different faculties.

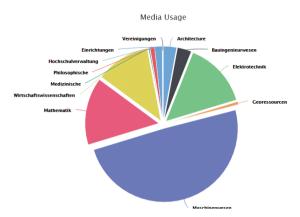


Figure 3 Overall media use among the faculties

On the other hand, the usage numbers are not normalized and correlated with number of students for each faculty, these numbers are understandable and expected. The Faculty of Mechanical Engineering is the biggest faculty at RWTH Aachen University. Furthermore, what was surprising for us was that the Faculty of Architecture relies on media resources. As it can be seen from Figure 4, one third of their usage falls under media usage. After this follow the faculties for Mechanical Engineering, Electrical Engineering, Economics,

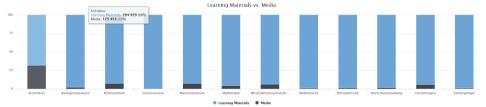


Figure 4 Learning Materials vs. Media Resources per faculty

and Mathematics, Informatics, and Natural Sciences. Their media usage ranges from five to eight percent in comparison with "classic" learning materials. The faculties for Civil Engineering, Geology, Philosophy, and Medicine fall further behind with only one percent. This information could be used to investigate in more details how each faculty implements its video-based learning, and thus allocate more resources and support in their direction.

The third scenario is more general and shows how many users and requests the learning platform has on daily basis; with what kind of devices the users use the learning platform; and which parts of the learning platform are used over one year. This visualization is important for the IT Staff to better scale the hardware, for the rectorate in order to grasp just how many different users rely on the learning platform on daily basis. Figure 5⁴

⁴ The troughs which go to zero in the visualization are points in time with missing log data.

represents a logarithmic representation of the daily requests and unique clients that there are on the platform every day. On weekdays, there are from $16 - 22\,000$ unique clients (users), and 1.5 - 2.5 million requests, while on weekends the numbers drop to 8-10 000 unique clients, and 0.5 - 1.2 million requests. This overview of unique clients and requests we explored it into two directions, namely the distribution of different devices and the amount of usage of different parts of the platform.

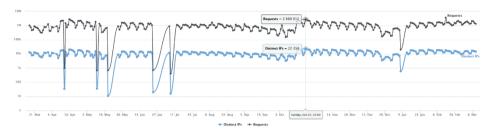


Figure 5 Unique clients and requests on the platform

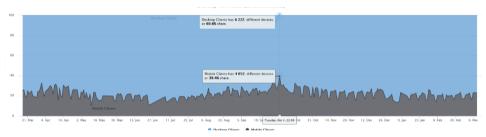


Figure 6 Desktop and Mobile devices on the platform

As it can be seen from Figure 6, on regular basis around 25 percent of the use comes from mobile devices. At the beginning of every semester there are peaks (sometimes around 30-40% of the devices are phones, or tablets) which can be explained with the fact that the students are looking and registering for courses and lectures, and are trying to organize their course work for the semester. This visualization is significant for the development team, because with it they can analyze the usage behavior based on different devices in order to provide better mobile compatibility and support of the platform's interface.

The course room structure of the learning platform consists of six domains: Organization,

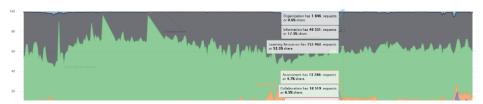


Figure 7 Course room domains use on the learning platform

Information, Learning Resources, Assessment, Collaboration, and Management. Each domain contains modules connected to its domain. Figure 8 shows an aggregated view of how these six domains of the course were used. The two domains with highest usage are the learning resources and information distribution, amounting to 70-80 percent of the use. They are followed by the collaboration and assessment domains, which each see usage ranging from four to ten percent each. One can further drill down in these domains, too see the distribution, participation, and presence of each faculty on the learning platform.

This visualization is useful for the eLearning committee and the coordinators, to understand that the most important activities of the students are timely information and learning resources distributions. They can drill-down into the data, and understand more how each individual module of each domain fares in the information and resources distribution. This information could be used to provide feedback and guidance to the faculty and students about strategies how to optimize their eLearning processes.

These three use cases complemented with visualizations show that the analytics tool can provide not only overview, but also insight and information about the implementation of the blended learning initiatives in HEI. Additionally, we do not provide possible solutions, actions, or decisions after we have presented the analytics, but leave this step for the users from the stakeholder groups.

5 Next Steps

This is the first iteration in the development cycle of the analytics prototype. We have put considerable thought to meet the expectations and the goals of our stakeholders, but we have not evaluated it with them yet. Thus, the fourth phase of the process, findings confirmations, is missing. However, we have already conducted some unofficial testing and test-usage with different people from the user groups, and the first reactions are very positive. Additionally, we are submitting a demo to the DeLFI conference and we would like to use this opportunity to collect additional feedback about our prototype. Currently, we are planning and preparing the evaluation of the prototype and a pilot phase with selected users. The plan is to develop several iterations of the prototype, and use the pilot phase to test different interfaces, indicators, and visualizations. The goal is to transform the tool from a prototype to production tool/service. The participants in our pilot phase will be blended learning coordinators, developers, and the team for support and qualification. Results from this evaluation phase can be presented at the conference demo and presentation.

6 Conclusion

In this paper, we presented a practical approach, how to introduce data-driven decision making in higher education in Germany. We started by examining the benefits of datadriven decision making and identifying that this is still a novel approach with development potential. Furthermore, we recognized the different stakeholder groups from the administration that will benefit from tools that can provide actionable intelligence and help them create informed decisions. We collected the perspectives and goals of these user groups, and discovered that they did not have any tools which could systematically support them in their work. Based on this work, we implemented the AiX Analytics prototype. This analytics prototype uses the log data from the learning platform to provide analytics and actionable intelligence to the identified stakeholder groups, and support them through the decision-making processes regarding the eLearning Initiatives and activities at RWTH Aachen University. We already received positive feedback and reception of the prototype, and currently we are planning a pilot phase and evaluation. These activities should provide feedback and results to improve the prototype, and provide this tool as a service for the administration evaluating their blended learning strategy. Additionally, we are going to share our experiences in analytics evaluation and implementation of data privacy compliant solutions in a production environment.

References

[CDO07]	Campbell, J. P.; DeBlois, P. B.; Oblinger, D. G.: Academic Analytics. Educ. Rev. 42, S. 40–57, 2007.
[Ch12]	Chatti, M. A.; et al.: A reference model for learning analytics. Int. J. Technol. Enhanc. Learn., 2012.
[Cr06]	Creighton, T.B.: Schools and Data: The Educator's Guide for Using Data to Improve Decision Making (2nd ed.), 2nd Editio. Aufl.: Corwin, 2006.
[Dy14]	Dyckhoff, Anna Lea: Action Research and Learning Analytics in Higher Education, 2014.
[Ho12]	Hollingworth, L; et al.: Data-driven decision making in higher education: One university's process of revamping the superintendent licensure program. J. Res. Leadersh. Educ. 7/1, S. 78–97, 2012.
[Ko08]	Kowalski, Theodore: Data-driven decisions and school leadership: best practices for school improvement. Pearson/A and B: Boston. 2008.