

Digitalisation of Education: Application and Best Practices

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Table of Contents

Digitalisation of Education: Application and Best Practices	1
Introduction	1
1. Learning Management Systems	2
2. Massive Open Online Courses.....	3
3. Learning analytics dashboards and visualisations	4
4. Data-supported feedback.....	5
5. Student misconceptions.....	6
6. Identifying at-risk students and predictive analytics.....	7
7. Student strategies and attitudes.....	8
8. Learning in a social context.....	9
9. Learning analytics and learning design	12
References.....	14

Introduction

The topic of digitalisation of education has attracted the interest of the research community worldwide due to unprecedented capabilities provided by the technology to capture the ‘digital traces’ of today’s students who, being ‘digital natives’, are active in technology-rich learning environments. The aim of this report is to present solutions on the topic that can be applicable to Swedish context. These solutions emerge as best practices or examples derived from searching the recent international literature. They can be adopted or modified to fit the Swedish context, given that it is rare to find universal solutions that can be applied ‘as-is’ (i.e., directly) in every socio-cultural context.

This report comprises ten different applications on digitalisation of modern education, which in their majority are relevant to *Learning Analytics*, defined as “the measurement, collection, analysis and reporting of [big] data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs” (Long & Siemens, 2011, p. 34). Learning analytics evidence for learning has earlier been validated and presented according to four propositions:

- Learning analytics improve learning outcomes
- Learning analytics improve learning support and teaching
- Learning analytics are taken up and used widely, including deployment at scale
- Learning analytics are used in ethical way (see Ferguson & Clow, 2017; Viberg et al., 2018).

First, this report touches upon some best practices of digitalisation in conjunction with some prominent learning technology, in particular with Learning Management Systems (LMSs), Massive Open Online Courses (MOOCs), and learning dashboards (sections 1-3). The second category discusses the use of learning analytics with a focus on addressing particular problems (sections 4-7): provide timely and relevant feedback, destabilise student misconceptions, help students develop effective learning strategies, and identify at-risk students with the aim of reducing drop-outs. Finally, two interesting and relevant themes are discussed which are closely related to curriculum design (sections 8-9): the interplay between learning analytics and learning design, learning analytics in a social learning context. It should be noted that the research studies mentioned in one category might also fit to some other category.

In addition to the relevant literature, the report is particularly inspired by recent reviews of learning analytics: Viberg et al. (2018), Misiejuk & Wasson (2017), and Lang et al. (2017). These reviews suggest that there are several research gaps in the area of learning analytics. They currently include the application of learning analytics in K-12 education, research on everyday analytics in classrooms, research on assessment, research on learning-centric analytics, as opposed to learner-centric analytics, implementation and impact of learning analytics and data literacy, with the exceptions of a few studies that address whether or not stakeholders (i.e., teachers and learners) can understand the visualisations they are presented (Misiejuk & Wasson, 2017). Most of the learning analytics research has so far been conducted in higher education.

1. Learning Management Systems

Learning Management Systems (LMS; e.g., Moodle, Blackboard, Canvas) are virtual learning environments that are being widely used in many different educational settings. Trace data about students' activity in a LMS are often at the heart of learning analytics applications. For example, Gašević et al. (2016) have shown that only the following variables - number of logins and number of operations performed on discussion forums and resources - were significant predictors of academic performance, predicting approximately 21% of the variability in academic performance. Hence, it is difficult to translate these predictors into actionable recommendations to facilitate student learning. An answer to this issue is offered by Nguyen et al. (2018), who argue that the key to actionable insights is the association between learning analytics with learning design. This association enables the teacher to compare and contrast the actual online behaviour of the students with the teacher's intentions. It is further described in section 9 on learning analytics with learning design.

Learning analytics have been shown to make extensive use of trace data from learners interacting with LMSs, and one of the most common uses is to derive an estimate of *the time each learner spent on task*, that is engaging in particular learning activities. Kovanovic et al. (2015) present two experiments exploring different measures of time on task; one using data from a fully-online course at a Canadian university, and another using data from a blended course at an Australian university. Based on modelling different student performance measures with popular statistics methods in two data sets, the results show that time-on-task measures typically outperformed count measures for predicting student performance, but more importantly, identified that the precise choice of time-on-task measure "can have a significant effect on the overall fit of the model, its significance, and eventually on the interpretation of research findings" (p.105). In summary, time-on-task estimation methods were found to play a considerable role in shaping the finals study results, especially in online environments where the amount of interaction with LMS is usually higher. From a practical perspective, researchers recommend to develop "standardized plugin for the extraction of

trace data from popular LMS systems (e.g., Moodle, WebCT, Canvas) that could provide fast and easy to time-on-task and count measures” (Kovanovic et al., 2015, p.105). Today, we still need such automatized tools that could be smoothly integrated into existing LMSs to better understand how learners spend time on their learning activities and thus to create better opportunities for their effective learning.

2. Massive Open Online Courses

Massive Open Online Courses (MOOCs) are available to thousands of students via some web-based platform, increasing access to high-quality material for distance and lifelong learners. MOOCs create large amounts of data can feed the various learning analytics tools. However, most MOOCs still adopt a top-down teaching approach, ignoring the potential for facilitating awareness, self-regulation and personalisation (Drachsler & Kalz, 2016). Drachsler and Kalz (2016) described the potential of learning analytics in the context of MOOCs. In particular, they describe a MOOC Learning Analytics Innovation Cycle (MOLAC; Figure 1) which can be applied at the micro, meso, and macro level.



Figure 1. The MOOC Learning Analytics Innovation Cycle (adopted from Drachsler & Kalz, 2016)

On the micro-level, the data collection and analytics activities are focused on individual reflection and individual prediction. On the meso-level, data from several open courses are combined to support benchmarking and to create insights about behavior of groups of learners rather than the individual. Finally, on the macro-level, cross-institutional learning analytics enables to develop learning and teaching interventions that can be tested in a cluster of educational institutions to analyse the impact of such interventions, beyond contextual factors. In their review of MOOCs and learning analytics, the authors pinpoint that presently most of the conducted studies focused on the micro-level of the MOLAC cycle.

A challenge with MOOCs is that, unlike traditional educational systems, measures like detailed demographics and prior knowledge are not collected in order to maintain a low barrier to entry. Many MOOC-providing institutions thus have begun to collect this data through optional surveys. Students completing their courses are also those who tend to complete these surveys. Reich (2014) suggest that roughly one quarter of enrolled learners fill out such course surveys. The volume of collected responses can be high (often tens of thousands) but might represent a skewed sample of generally more motivated learners.

With respect to students' *affective domain* (i.e., the domain that includes the manner in which individuals manage things emotionally, for example values, feelings, and appreciation), Leony et al. (2015) built four models to detect boredom, frustration, happiness, and confusion in MOOCs. The models were tested on a group of students and the correlation between the emotions and student's interaction data was calculated. The four suggested models have been implemented into ALAS-KA, a learning analytics module for the Khan Academy platform. This module includes new metrics (except those already provided by the platform) and visualisations of information taken from the analysis of the user activities' patterns. All of the implemented modules take into account the ProblemLog provided by the Khan Academy. It includes all of the information about users' interaction with exercises and the timestamp in which they took place. The four models were applied on the 90 students taking the courses in mathematics, physics and chemistry in 2013. The initial analysis of emotion values calculated for a period of 10 days has shown several expected patterns, such as increments of emotion levels as learners were interacting more with the course materials. The use of rules for the detection can help to overcome several issues, including a slow start, given that at an initial moment there might not be enough data to calculate the learners' emotions values. By adding the logic to the inference of each emotion, educational instructors can be aware of the metrics that could have interfered to be able to detect a chosen emotion in a learner and thus to make better informed decisions.

3. Learning analytics dashboards and visualisations

Learning-analytics dashboards (LAD) are currently the main trend in the literature since they mirror the students' behaviour back to the students and/or to the teachers. Learning dashboard is defined as "a single display that aggregates multiple visualisations of different indicators about learner(s), learning process(es), and/or learning context" (Schwendimann et al., 2016).

Millecamp et al. (2018) present a LAD that supports the dialogue between a student and a study advisor. To ensure transfer to other contexts (in terms of scalability), the dashboard visualises data that is commonly available in higher education, like the grades of the student, study progress, and academic ranking in comparison with peers (i.e., social comparison), and a prediction of the duration of study for the bachelor program for this student, based on historic data. A dashboard was deployed at KU Leuven (Belgium) to support discussion sessions. The results indicate that the dashboard primarily triggers reflective conversations with students doubting to continue the bachelor program, indicating that the dashboard is useful to support difficult decision-making processes.

Another example presents the Student Activity Meter (SAM) for *awareness* and *self-reflection* (Govaerts et al., 2011). SAM visualises learning activities within online learning environments for learners and teachers to help increase awareness and to support self-reflection. This dashboard supports the following teacher objectives:

- Awareness for teachers of what and how learners are doing is important to assess learners progress
- SAM visualises the time learners spent and the resources they used
- Time tracking information allows teachers to assess their initial time estimates with the real time spending of the students and find the exercises that consume most time
- The resource usage can show the popular learning materials and enables resource discovery, through a list of most used or most time spent on resources in SAM.

The results of the conducted case study show that SAM contributes to creating awareness for teachers. It enables: i) to find students doing well and at risk, ii) a better course overview, and iii) understanding student time spending. Most of the participants wanted to continue using SAM.

Broos et al. (2017) introduced a LAD for actionable feedback on learning skills. The dashboard provides actionable feedback about five of the learning skills assessed by the Learning Analytics Study Strategies Inventory (LASSI): *concentration, anxiety, motivation, test strategies, and time management*. It uses data about students, their learning skills and scores that were already available with the institution (KU Leuven), but fragmented across services and not fed back to the data subjects (i.e., learners and teachers) in a direct way. 1406 1st year students in 12 different study programs at KU Leuven were invited to use the dashboard to support them in their transition from secondary to higher education. The LASSI was used to assess learning skills using a survey taken within the first weeks of the academic year. The dashboard system (for the high-level overview of the system see Figure 2) did not require direct access to the students' names or other characteristics that allow for straightforward identification, as they were made available at access time by the single-sign on infrastructure.

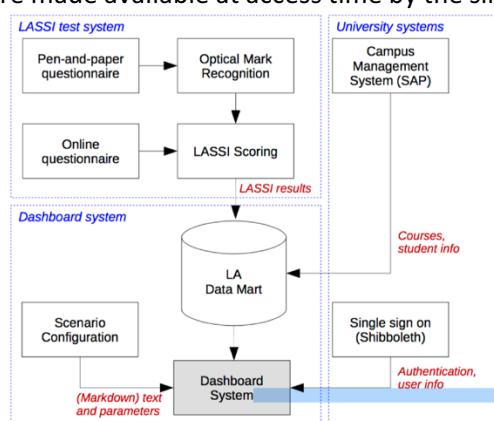


Figure 2. Overview of systems and data flows to support the dashboard (adopted from Broos et al. 2017)

The system logged access to and behavior within the LAD and analysed their relationship with these learning skills. The results show that while 8 out of 10 students accessed the LAD, students with lower time management scores tend to have a lower click-through rate. Once within the dashboard, students with lower scores for specific learning skills are accessing the corresponding information and remediation possibilities more often. Regardless of their scores for any of the other learning skills, learners with higher motivation scores are reading the remediation possibilities for the other four learning skills more often. Gender and study program were found to have an influence on how learners use the LAD.

4. Data-supported feedback

The provision of timely and relevant feedback is another topic closely associated to the use of learning analytics. Kickmeier-Rust et al. (2014) developed a gamified learning app, 'Sonic Divider'¹ to help primary school students in Australia learn mathematics. It features formative assessment and feedback functions and gives the teacher a quickly overview about the achievements, scores, and competency levels. The authors examined the link between formative feedback and learning performance, and analysed the results by gender and overall

¹ Sonice Divider, <http://next-tell.eu/portfolios/sonicdivider/>

by statistical methods. They found evidence for the motivational aspect of the gamification elements, in particular scoring. They also identified positive effects of an individualized and meaningful, elaborated feedback about errors made. With respect to gender differences, the authors found evidence that girls were less attracted by competition elements (e.g., by comparing high scores) than boys, however, they were more attentive towards feedback coming from the tool.

“*Learning is personal (LIP)*”² is another available tool that offers data-supported feedback. The LIP tool captures learning activities in real-time and provides instant statistical feedback. It mainly targets teachers, students and students’ peers. In particular, it supports learners’ peer- and self-assessments as well as teachers’ observations. It is optimized to fit classroom activities where time and attention are scarce resources. The tool’s focus is to provide an overview over all learning activities in all subjects over the whole term. It does not provide specific insights or in-depth analyses. However, it provides the teacher with simple, real-time insights and allows the teacher to enhance the data model (e.g., used material) on the fly. This tool is optimised for performance and to be on tablets, mobiles and laptops.

5. Student misconceptions

Students’ misconceptions about a subject might be deeply-rooted and can impede learning, which suggests that the practice of only considering the final solution often results in student knowledge gaps and misconceptions (Davies et al., 2015). The area of *intelligent tutoring systems*³ (ITS) has a long tradition in clarification of misconceptions and personalisation of learning (e.g., personalised feedback).

Davies et al. (2015) compared differences in detecting students’ knowledge gaps and misconceptions about the use of absolute references⁴ when using assessment-level data (i.e., the final solution students submit when solving a problem) to that of using transactional-level or activity-trace data (i.e., the process students take to arrive at their final solution). In their study, the researchers – based on the analysis of the student assessment data (i.e., their written homework, mid-term examination and final exams) collected from three universities in the western United States in 2014 (995 students) - found higher levels of knowledge components gaps and misunderstandings when assessing transactional-level knowledge component data than task-level final solution data.

Data was gathered through an ITS, in this case a tool developed in the Microsoft Excel platform: for each assignment, the developed system created a specified log of each step the student took to come to a solution, i.e., not only the final solution graded by the program. The log was then recorded on a hidden worksheet within the workbook so that when the student’s solution is submitted the log is submitted as well. This log can then be extracted for analysis of the student’s learning process and the final solution.

Examining the final solutions that students submitted showed little evidence that students had any misunderstandings or knowledge gaps about the use of absolute references. Nevertheless, analysing data at the transactional level researchers identified that far more students struggled using absolute references than the analysis of only the final solutions. In

² LIP tool, <http://next-tell.eu/portfolios/learning-is-personal-lip/>

³ Intelligent tutoring system is a computer system that aims to provide immediate and customised feedback to learners.

⁴ For more information about absolute and relative references, see <https://edu.gcfglobal.org/en/excel2016/relative-and-absolute-cell-references/1/>

particular, the findings revealed that students not only struggled to solve the problem requiring the use of absolute references, but also they tried to use absolute references when they were not needed. This was not detected when analysing just final assessment data.

All this suggests that once data is understood through data mining it can be used to make decisions in regard to *when* and *how* to intervene in the learning process. The study's implications highlight the potential of making adaptations to instruction, providing feedback and remediation, and also improvements in the ability to diagnose knowledge gaps that influence student comprehension. For researchers and practitioners there are several *challenges* to be considered when attempting to analyse students' misconceptions:

- Getting the right data is vital! (i.e., in the aforementioned case, transactional level data)
- When collecting data, meaningful data logging procedures should be established in advance; this includes capturing pertinent data that can be linked to other information, e.g., systems level data. At this point data must be extracted and analysed manually (Davies et al., 2015).

6. Identifying at-risk students and predictive analytics

The identification of at-risk students has received much attention and it has been frequently associated with a special category of learning analytics named *predictive analytics* which is focusing specifically on that aspect. However, the number of initiatives that have been able to transition from concept to implementation is still scarce (Jayaprakash et al., 2014, Viberg et al. 2018). The *Course Signals* project at Purdue University (Arnold & Pistilli, 2012) is a successful application of predictive modelling to student completion in higher education. The Course Signals system has been developed on the idea that students do not have a good understanding of how they are progressing in their studies/courses. Purdue developed their approach to "early warning systems" which shows at-risk students over several years.

The predictive model used is based on four components: demographic characteristics, previous academic history, interaction with the LMS/VLE during the course and performance on the course to date. The predictions from the model are translated into a signal: green, denoting a high chance of success; yellow, denoting potential problems; or red, denoting a high chance of failure. Teachers run the model and generate signals for the students on their course. The teacher can then choose what interventions to trigger: sending a personalised email or text, posting the signal on the LMS. Purdue piloted Course Signals in 2007 and it became automated in 2009. In 2012 around 24000 students and 145 educators have used Course Signals in at least one of the courses. Key points include: i) problems are identified as early as the second week in the semester, iii) feedback is categorised as motivational or informative, iii) students using Signals seek help earlier and more often, and iv) one of the study's results showed 10% more As and Bs were given for courses using Signals compare for previous courses which did not use the Signals system. Overall, students liked Signals: 89 % of them considered it a positive experience and found the combination of the traffic signals and instructor feedback to be informative and motivational. Anticipated problems with Signals included maintaining the privacy of teaching performance and ensuring the validity of the algorithm. As pointed out by the earlier research (JICS, 2017), several issues have to be taken into consideration when designing and implementing similar systems:

- Students did not express concerns about privacy about their data but that did not mean that the institution should not neglect to protect it.

- Institutions need to be able to extract data from different systems efficiently and timely.
- Given the centrality of student success to the institutional mission, learning analytics efforts might be better initiated and led from an education-focused unit than from the IT-department.

Based on the success of the Signals systems, researchers at the Marist College in the US (Jayaprakash et al., 2014) implemented the Online Academic Analytics Initiative (OAAI) that aimed to help students, identified as ‘needing help’, to engage them in an online community designed to help them to succeed academically. The OAAI developed a prototype of an open-source academic earlier alert system that feeds from the Sakai CLE (Collaboration and Learning Environment), and includes open predictive model based on the Pentaho Business Analytics suite (an open source analytics suite with data mining and data integration capabilities), and intervention strategies that leverage Open Educational Resources. The predictive goal of the developed system was to detect early those undergraduates who were in academic difficulty in the course by using student data. Four sources of data were considered: i) student demographic and aptitude data, ii) course grade and course related data, iii) Sakai-generated data on student interaction with the LMS and iv) partial contributions to the student’s final grade collected by Sakai’s gradebook tool, i.e., grades on specific grading events, e.g., assignments and exams. The pilots were run in Spring 2012 and Fall 2012. Student identified at risk, were subjected to 2 interventions strategies: “Awareness Messaging” and participating in on “Online Academic Support Environment”. In one course at Marist College there was a significant improvement in final grade (6%) with those at-risk students who were subject to an intervention compared with those in the control group, who were not.

7. Learning strategies

Developing students’ learning strategies and attitudes is intriguing because it involves higher-order thinking skills on behalf of the students, like self-regulated learning (SRL) and critical thinking. While the importance of SRL to learning is recognised, understanding how SRL is applied in context is not a simple task (Roll & Winne, 2015). To realise the potential of learning analytics for advanced of the learning sciences, we need: i) to develop instrumentation to record traces of SRL across all its phases, ii) to develop and to test methods that identify structures within data, iii) to explore the effects of interventions (Roll & Winnie, 2015).

One of the successful applications of learning analytics to improve students’ SRL skills refers to the study by Tabuenca et al. (2015). In this study, the researchers investigated students’ time management skills as the part of their SRL, and in particular examined the effects of tracking and monitoring time devoted to learn with a mobile tool on SRL. 26 students enrolled in two online courses from two universities in the Netherlands participated in the study. The LearnTracker Backend Database model has been used. From the student activity point of view, the system hosts the timestamp and duration of the learning activity (for more see Tabuenca et al., 2015). LearnTracker offers mobile support for students enrolled in online courses in which the learning goals are predefined by teachers. Courses deployed in LearnTracker are retrieved from the remote database at LearnTracker Backend. Similarly, time-logs are also recorded in the backend. LearnerTracker also provides social learning analytics contrasting the time devoted by the student with the time devoted by his peers, as well as the time originally estimated by the teacher. The experiment aimed to estimate how accurate estimations by instructional designers are with regard to the time needed to

accomplish each learning activity scheduled in a course. Time-logs records during the course and the grades obtained in the final evaluation were taken as indicator. The study's findings show that using mobile devices to log and track the time devoted to study across contexts (formal and informal) might lead to an improvement on time management skills and showed that notifications pushed at random time of the day do not produce significant improvements in time management.

Researchers have also examined the development of students' reflection skills through a game-based approach called the "Trails of Integrity and Ethics" (TIEs; Kwong et al., 2017). A total of 658 students from four Hong Kong institutions participated in the study between October 2016 to December 2016. This approach uses focused scenarios on ethical dilemmas - coupled with Augmented Reality (AR) and mobile technologies - to design TIEs where scenarios are triggered in various locations and students are challenged to review the arguments presented and reflect on their ethical choices. In particular, students played out the consequences of their decisions which help strengthen the links between the theoretical concept of academic integrity and ethics as well as the practical application in daily settings. Contents of all scenarios are designed based in the 3C model, i.e., each decision making scenario has to include a *Challenge*, *Choices*, and *Consequences*. All TIEs are deployed using a mobile application Mobxz⁵, a service designed specifically for learning trails and supporting both iOS and Android smart devices. Students use their mobile devices to walk through a trail and activate the learning activities within each checkpoint scenario marker-based (e.g., QR code) and marker-less (e.g., GPS location mapping), AR technologies that are built-in in this mobile app. To evaluate the effectiveness of TIEs, triangulation of different data sets was adopted, including experience surveys, qualitative feedback, clickstream data and text mining of pre/post-trail discussion. The results indicated that students' interests in learning about issues of academic integrity and ethics in classrooms were stimulated.

This study - using clickstream data collected from mobile devices - presents an example of the research, employed at scale, in the area of learning analytics and shows positive learning evidence. Such studies are limited (Chan et al. 2015) and should be thus seen as exemplars. "With enough evidence showing students can effectively learn the concepts of AIE [academic integrity and ethics] using the TIEs [Trails of Integrity and Ethics], others in the education sector, such as secondary schools can be encouraged to get involved" (Kwong et al., 2017, p. 367).

8. Learning in a social context

With respect to digitalisation of data, learning in a social context pinpoints the emergence of social learning analytics (SLA). SLA emphasizes the concept of social network analysis on learning activities and employs methods of learning analytics to student groups instead of individuals as a scope for analysis of learning activities (Haya et al., 2015, p. 303). Ferguson and Buckingham Shum (2012) suggest five approaches to SLA.

- Social learning network analytics: a successful example of this category is the SNAPP⁶ (Social Networks Adapting Pedagogical Practice) tool, which is a visualisation tool for LMS forums. It can be used to identify disconnected students and indicate the extent to which a learning community is developing within a virtual learning environment.

⁵ Mobxz, <https://mightysignal.com/a/ios/618295647>

⁶ SNAPP tool, <https://github.com/aneesha/SNAPPVis>

- Social learning discourse analytics: an example is the Cohere tool,⁷ which is a web application providing a medium for engaging in structured online discourse, or for summarising/analysing it, e.g. as a moderator, educator or researcher. Figure 2 shows how Cohere augments common online dialogue text: the icons at the side of each post shows rhetorical role of the post and the semantic connections the rhetorical move between posts (De Liddo et al., 2011).
- Social learning content analytics: when viewing online resources, SocialLearn's 'Backpack' – a toolbar of apps and resources – can be used on any Internet site. The Backpack currently includes the basic components of social learning content analytics. It provides, among others, the option of viewing the keywords, hotlinks or images connected with the open web page. In particular, when clicking in the Backpack's light bulb icon provides the option of viewing the keywords, hotlinks or images connected with the open web page (as in the large box on the right of Figure 3). The information about images can be merged with visual similarity search to identify and recommend other resources that make use of these images,



Figure 3. The SocialLearn Backpack open at the foot of a BBC News page, showing a list of images on the page (adopted from Ferguson & Buckingham Shum, 2012)

- Social learning disposition analytics. Learning dispositions can be modelled as a multi-dimensional construct called Learning Power, currently assessed by learner self-report via a web questionnaire called ELLI (Effective Lifelong Learning Inventory⁸), whose data warehouse platform supports a range of analytics (Ferguson & Buckingham Shum, 2012). ELLI generates a spider diagram visual analytic which is used to support self-reflection and change. ELLI has been validated and piloted at the Open University (UK; Edwards, 2011).
- Implementing social learning context analytics: the SocialLearn app recommends and provides access to learning materials in response to search terms. The app allows resources to be rated and recommended to individuals or to groups. If users choose to make their location data available, this can be used to influence recommendations; for example, if Simon is working on 'Climate Change' the app might suggest a podcast on coastal defences when he visits a seaside resort, and could provide a map showing a local site where Simon would be able to view the effects of erosion.

⁷ Cohere tool, <http://cohere.open.ac.uk/>

⁸ Effective Lifelong Learning Inventory, <https://www.elli.global/>



Figure 4. Dialogues augmented with the Cohere tool

Haya et al. (2015) demonstrated a Social Learning Analytics (SLA) toolkit that applies social network analysis and content analysis techniques on forum messages to analyse collaboration among students and to support teacher inquiry. The SLA toolkit was integrated in the JuxtaLearn learning process and platform (see Figure 5).

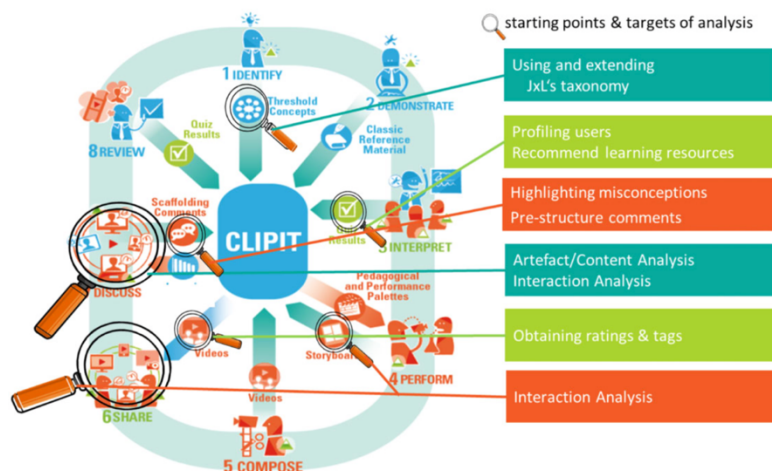


Figure 5. Learning Analytics-enhanced JuxtaLearn Process (adopted from Haya et al. 2015).

The authors adopted the *Teacher-led Inquiry into Student Learning (TISL)* pedagogical approach and practice that encourages teachers to systematically examine the effects of their learning design on student performance and learning. Learning Design refers to “the application of methods, resources and theoretical frameworks to achieve a particular pedagogical goal in a given context” (p. 302) and from a Learning Design point of view, the main challenge lies in integrating design tools used for lesson planning with tools for monitoring and analysis.

The research presents case studies that exemplify the key features of the TISL approach in the context of video created learning scenario and the kind of outcomes that can be obtained. In their study, Haya et al. (2015) explored the potential of computational methods to support

teachers and learners participating in collaborative scenarios. The researchers implemented a web space that supports networks of people, content and services based on the open-source social platform *Elgg* (<https://elgg.org>). This space provides *object-oriented programming* –the chosen for this study course – related communication through videos and ensuing discussions and comments. The platform supports uploading, archiving and sharing of learner-created content. Overall, the learning process is grounded in the student reflection in the three key areas: I) collaborative video production, ii) discussion and iii) peer evaluation. Discussion and evaluation are directly supported by the web space.

The case studies’ results show that the teachers can derive valuable insights into the students’ learning activities from analytics results. The authors (Haya et al., 2015) exemplify indicators for the quality of cooperation presented by communication (see e.g., Figure 6) or portfolio diagrams (see e.g., Figure).

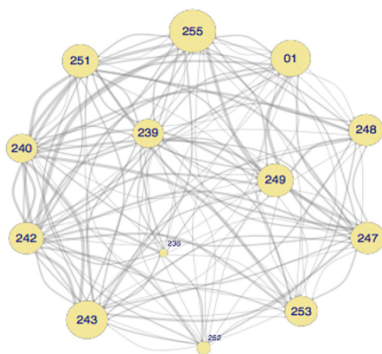


Figure 6. Discussion network

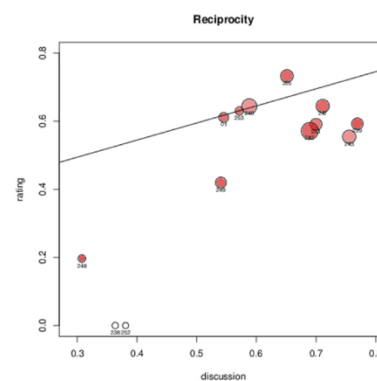


Figure 7. Reciprocity

Such diagrams allow for introducing thresholds for expected behavior indicating the need for intervention to teachers how are now familiar with these types of diagrams. For researchers and learning designers who become used to interpreting such diagrams they provide the opportunity to obtain detailed information about irregularities in the process, which may and in some cases, should lead to adaptations. The complementing application of content analysis methods, here Network Text Analysis helped to detect frequent misconceptions from student comments which inform learning designers and teachers about topics of interests. Moreover, additional indicators, such as the semantic richness measure, provide the bases for scaffolding students to keep focused on the domain-related learning task rather than aiming at producing ‘perfect’ videos. In summary, the toolkit supports multiple levels of analysis that provide deeper insights into the collaborative learning process

Berland et al. (2015) introduced *AMOEBa*, a collaboration orchestration tool to support programming learning activities in high school by supporting teachers to pair students based on real time analyses of students’ programming progressions. The results showed that using *AMOEBa* to help with pairing students resulted in improvements in the complexity and depth of the student’s programs.

9. Learning analytics and learning design

The interplay between learning analytics and learning design has recently attracted the interest of researchers mainly for one reason: to check whether there are discrepancies between the students’ actual behaviour and the teacher’s intentions, and in turn, to make corrective actions. For example, the study of Nguyen et al. (2018) used trace data from the

Moodle LMS to investigate to what extent students' timing of engagements aligned with instructor learning design, and how engagement varied across different levels of performance. The analysis was conducted over 30 weeks using trace data (from an online course at the Open University, UK) on 387 students and replicated over two semesters in 2015 and 2016.

The data analysis was performed via visualisations and multilevel modelling. To understand *to what extent do students' timing of engagement align with instructors' learning design* visualisations were employed. Firstly, actually study patters against the learning design were visualised. Secondly, the study patters for respective individual study materials across excellent, passed, and failed group. The visualisations were conducted using Jupyter Notebook⁹ and Tableau¹⁰. To compare study patters across three groups of performance over time, a multilevel modelling (or mixed-effect modelling) approach was used. This approach, compared to the traditional repeated measure ANOVA approach, allows for missing data, tolerates differently spaced waves of data (e.g., due to Christmas break) and allows for nonlinear relationships (Nguen et al., 2018, p.144).

Their findings revealed a mismatch between how instructors designed for learning and how students studied in reality. In most weeks, students spent less time studying the assigned materials on the Moodle platform compared to the number of hours recommended by instructors. The timing of engagement also varied, from in advance to catching up patterns. High performing students (i.e., the passed and the excellent groups) spent more time studying in advance, while low-performing students spent a higher proportion of their time on catching-up activities. Towards the end of the course, the gap between failed and passed/excellent students increased considerably.

In summary, by comparing and contrasting the assumptions in learning design made by instructors with actual student behavior, learning analytics could act as a reflective source and provide actionable feedback. One potential implication of this study is if students tend to spend more time on catching up a particular learning material, the instructors could check whether the material was clearly explained, and provide a quick review.

Rodríguez-Triana et al. (2015) present the monitoring-aware design process, which describes the steps that teachers should undertake during the design of computer-supported collaborative learning scenarios, in order to reflect on their monitoring needs and express expectations about students' interaction. From a learning analytics perspective, monitoring examines students' interactions during the enactment of the learning scenarios and facilitates the intervention on the situation toward a more productive direction (Rodríguez-Triana et al., 2015). The authors adopt the following learning design-aware monitoring process:

1. Collect interaction data, guided by the underlying learning design (e.g., participants, resources, and/or deadlines).
2. Create indicators to construct a model of desired interaction (i.e., students' interactions with the learning system) based on the learning design definition and constraints, and the teachers' decisions.
3. Compare actual and desired states of interaction i.e., comparing the gathered evidence with the learning design definition and constraints.

⁹ <https://jupyter.org>

¹⁰ <https://www.tableau.com>

4. Advice or guide the interaction, by informing teachers about discrepancies about the actual and the desired state.

To deploy the strategy mentioned above, the authors used a number of tools; in particular, *First*, the Web-Collage tool¹¹ to create the learning in a digital format; then, *the GLUE-PS*¹² tool (i.e., Group Learning Unified Environment - Pedagogical Scripting) - used by the teachers - deployed automatically the design into the distributed learning environments, i.e., different existing Virtual Learning Environments (e.g., Moodle); and a custom-made third tool, the Group Learning Interaction Monitor for Pedagogical Scripting Environments (GLIMSE) prototype, to track and report the interactions taking place in the LMS platform. GLIMSE took the script instantiation file generated by GLUE-PS and the XML version of the forms to guide the data gathering and analysis.

In summary, we have provided several relevant examples that might be applicable in the Swedish context, but to be able to understand further how learning analytics can improve different aspects of learning process and learning outcomes, practitioners need to consider several important questions such as: *What problems do we want to solve? What learner activities do we want to support? What kind of data, that we may, or may not have today, would be valuable to analyse? How the available methods and tools that are applicable on one educational context be relevant and useful in another context? What are the challenges? Are there any important ethical considerations that should be taken into account?*

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¹¹ Web Collage, <http://www.id-grid.org/resources/tools/webcollage>

¹² GLUE!-PS tool, <https://www.gsic.uva.es/glueps/>

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