Efforts in Europe for Data-Driven Improvement of Education

A Review of Learning Analytics Research in Seven Countries

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Abstract—Information and communication technologies are increasingly mediating learning and teaching practices as well as how educational institutions are handling their administrative work. As such, students and teachers are leaving large amounts of digital footprints and traces in various educational apps and learning management platforms, and educational administrators register various processes and outcomes in digital administrative systems. It is against such a background we in recent years have seen the emergence of the fast-growing and multi-disciplinary field of learning analytics. In this paper, we examine the research efforts that have been conducted in the field of learning analytics in Austria, Denmark, Finland, Norway, Germany, Spain, and Sweden. More specifically, we report on developed national policies, infrastructures and competence centers, as well as major research projects and developed research strands within the selected countries. The main conclusions of this paper are that the work of researchers around Europe has not led to national adoption or European level strategies for learning analytics. Furthermore, most countries have not established national policies for learners' data or guidelines that govern the ethical usage of data in research or education. We also conclude, that learning analytics research on pre-university level to high extent have been overlooked. In the same vein, learning analytics has not received enough focus form national and European national bodies. Such funding is necessary for taking steps towards data-driven development of education.

Keywords—Learning analytics, Europe, data-driven improvement, education

1 Introduction

Over the past decades, the world has undergone a transformation process, which many consider to be as important as the Industrial Revolution once. In this post-industrial society, also called the information and knowledge society, information technology plays a crucial role. It permeates and transforms how we work, study, relate to information and knowledge and how we spend our free time. As a consequence of this digitization, huge quantities of data, i.e. big data, is generated that reflects our activities. Therefore, in many fields, such as business or medicine, we have witnessed how essential the use of analytics has become to process generated big data in order to develop data-driven insights into people's activities for the optimization of processes and outputs.

Today, the educational systems around the world are also undergoing major digital transformations. Information and communication technologies are increasingly mediating learning and teaching practices as well as how educational institutions are handling their administrative work. As such, students and teachers are leaving large amounts of digital footprints and traces in various educational apps and learning management platforms, and educational administrators register various processes and outcomes in digital administrative systems.

It is against such a background we in recent years have seen the emergence of the fast-growing and multi-disciplinary field of learning analytics. The field, which originates from disciplines such as "*business intelligence, web analytics, educational data mining and recommender systems*" [1, p. 1) attempts to exploit data generated in educational settings "*for purposes of understanding and optimizing learning and the environments in which it occurs*" [2, p. 34].

Although the field of learning analytics is still in its infancy, seen from an international perspective, it has already produced innovative educational research that demonstrate the utility of learning analytics on the micro level (understanding and developing learning and teaching), on the meso level (understanding and developing single educational organizations), and on the macro level (understanding and developing on a national level or across educational organizations) [3, 4, 5].

From a European standpoint, the potentials of learning analytics were recognized early on. Already in 2013, only two years after the official birth of the field of learning analytics, the European Commission emphasized that learning analytics can contribute to "*develop new solutions for better personalised learning, by allowing teachers to have a more accurate and up-to-date follow up of each learner. Through learning analytics, new and more learner-centred teaching methods can emerge since the evolution of learners who use ICT regularly can be closely monitored."* [6, p.5). In another more recent report the European Commission Working Group on Digital Skills and Competences (ET2020) once again pointed to the potential of learning analytics to "*contribute to the quality of teaching and learning and the modernization of educational systems in Europe*." [7, p.2]. Moreover, ET2020 urged for capacity building in the field and collaborative research projects. And indeed, research in learning analytics is growing in Europe, especially from countries such as Spain, United Kingdom, Germany, Netherlands, and Austria. Furthermore, several European countries, such as Norway, Denmark, and Netherlands, are developing nationwide learning analytics strategies that includes infrastructure, competence centers, and national policies.

In this paper, we examine the research efforts that have been conducted in the field of learning analytics in Austria, Denmark, Finland, Norway, Germany, Spain, and Sweden. More specifically, we report on developed national policies, infrastructures and competence centers, as well as major research projects and developed research strands within the selected countries.

2 European Research

2.1 Austria

The research efforts in Austria has been started already back in 2011[1]. Based on personal meetings between George Siemens, Erik Duval and Martin Ebner at the ED-Media conference in Lisbon, Portugal, the idea of a conference on Big Data for Learning was shared to a large community - today, well known as International Conference Learning Analytics and Knowledge, shortly LAK. The second was done in Vancouver, Canada in April 2012[2]. At this conference, a first research work from Austria was presented and discussed - just a simple multiplication trainer for schoolchildren aged 8-12 years [8].

[1] https://www.aace.org/review/ed-media-2011-lisbon-portugal-final-call-for-participation-april-12/ (last visited June 2019)

[2] https://solaresearch.org/events/lak/#lak12 (last visited in June 2019)

The research team followed the idea to collect and gather all calculations done by the children and to give feedback to the learners as well as the teachers. Today the application holds more than 1.000.000 calculations and we know very precisely how the learning of the multiplication table is happening described in several publications [9] [10] [11].

In addition, the research team worked on more applications for school children - an addition, a subtraction [12], a division and a multi-digit trainer [13]. As follow up, Graz University of Technology contributed to a first European project about German spelling acquisition [14]. The project aims to offer children an online editor for writing short essay. In the background beside a typical spell-checking dictionary an intelligent one was implemented. This developed one holds words, written in all possible and false forms, categorized in different groups. The Learning Analytics part analyses each text and provide feedback to learners and teachers divided to the defined categories.

Beside this project in secondary education in 2014 first research has been done in higher and adult education. The University of Graz as well as the University of Technology of Graz founded in 2014 the first and till now online MOOC platform in Austria, called iMooX. Due to the fact that MOOCs are addressing a huge amount of learner's data driven investigations seems to be a logical step firstly described in detail in [15]. Different studies pointed out how Learning Analytics can help to identify different kind of learners [16], how students remain in MOOCs [17], how gamification elements assist the learning process [18] and even how new didactical approaches, called Inverse Blended Learning, are introduced [19].

Another joint project on European level between KU Leuven, University Nottingham, TU Delft and TU Graz called STELA ("**S**uccessful **T**ransition from secondary to higher **E**ducation using **L**earning **A**nalytics") aimed to assist students during their transition phase from secondary to higher education [20]. The outcome of the project provided a general framework for building students' dashboards [21] (Leitner & Ebner, 2016) and different prototypes at each single university.

Finally, there are also some work done on a policy level for national issues. Due to the fact that in Austria the data protection law is rather strong, it is from high importance to think about how Learning Analytics can be integrated on an institutional level. One first research work was about the de-identification of data [22] and general challenges to overcome if Learning Analytics will be introduced in Higher education institutions [23].

Currently a white paper on Learning Analytics for Higher Education is elaborated under the lead of the nationwide association of new media for teaching and learning. Finally, the ministry of education, science and research announced to give financial support for Learning Analytics applications in the next years.

2.2 Denmark

Learning Analytics as a field in Denmark seems rather as disconnected islands than as a connected whole. While research efforts within the scope of LA as defined in this article have been done for some time, research has until recently been conducted at separate universities and university colleges without much interaction and collaboration. Furthermore, the two overall aims for LA, understanding and optimizing seem to be a source of divisions in the Danish landscape. Some researchers focus on understanding from an educational standpoint [24], others on optimizing from a computer science standpoint [25]. In addition to this division, a third division seems to be between econometrics and educational research, where econometrics as a field is more interested in the effects of intervention and use educational test-data as outcome variables [26].

Also, worth mentioning, though not as such LA research, is a strand of research critically monitoring the consequences of the digital transformation of the Danish educational system, among other things, focusing on the consequences of integrating analytics into the ecosystem of public primary education.

Apart from divisions in terms of research focus, the divisions between educational research and econometrics is evidenced by public debates [27] in the wake of public reports on Danish national tests [28]. We speculate that the origin of this divide is determined by the broad field of the researcher; computer scientists engaging in LA are more likely to focus on optimizing, while educational researchers are more likely to link LA data to e.g. constructivist theories of learning. Econometrics seems to be narrowly focused on establishing causal relationships using linear models. Thus, we see a gap between (at least) three traditions: a computer scientist tradition, an econometrics tradition, and an educational tradition. Here, we provide examples to illustrate the LA landscape in Denmark and then present current or very recent efforts to begin bridging the gap.

The Danish Center for Big Data Analytics Driven Innovation (DABAI), was established in 2016, with learning analytics as one of the goals. Within the field, DABAI is to pursue optimization of e-learning personalization, student behavior modeling, predicting student performance, similarity among quizzes, authorship verification, and curriculum trainer [25]. With regards to student behavior modeling, researchers have created a model of student drop-outs in Danish upper secondary school.

Another avenue of research in play is a design-based approach. Here, educational researchers design online and blended learning materials for science courses while at the same time monitoring clickstreams, videotaping lessons, and audiotaping student discussions for joint multimodal analyses [29]. On such project is the Virtual Neutrons for Teaching project (eneutrons.org), in which students learn neutron scattering via online textbooks and quizzes [30] [31]. One of the outcomes of the projects is a novel method for analyzing online student behaviors using clickstream data [32].

Two large ongoing projects, both funded by Innovation Fund Denmark (Innovationsfonden), are also worth mentioning. The first, Game-based Leaning in the 21st Century (GBL21), is a large collaborative project aimed at developing design thinking skills through game-based learning (https://gbl21.aau.dk). As a part of GBL21 educational researchers from DPU, Aarhus University and Aalborg University are developing an online tool for assessing different aspects of design thinking skills. The other project, Automatically Tracking Early Stage Literacy Skills (ATEL), involves researchers from DPU, Aarhus University and Technical University of Denmark (DTU) collaborating on developing analytics tools for tracking early stage literacy development (

Furthermore, in 2010, Denmark implemented national tests in grades 2-4 as well as 6-8 in primary school. The tests are obligatory and target different subjects in different grades (https://www.uvm.dk/folkeskolen/elevplaner-nationale-test--trivselsmaaling-og-sprogproever/nationale-test/klassetrin-fag-og-profilomraader). The tests are adaptive, meaning that each student will be presented with test items during the test-period (usually 1 hour in-class) and that the difficulty of test item i+1 is dependent on the student answer to test item i. The system collects data on the students, which is used to monitor, single students, classes, and schools. While in-depth analyses are possible, research seems to have focused mainly on macro-scale variables, such as whether there is a positive or negative effect of the national tests.

We have argued that in Denmark, a gap between LA as undertaken by computer scientists, econometrics researchers, and educational researchers exists. We believe that in order to bridge this gap, computer scientists will need to learn to operationalize current educational theories and results, while educational researchers need to utilize and interpret results from currently used computer algorithms. The gap between educational researchers and econometrics researchers seems to be rooted in substantially different aims and methods for the two fields. Bridging all of these gaps will require extensive cooperation and probably compromises.

Despite the lack of coherence and collaboration in the Danish LA research community, there are, however, efforts to connect to the larger Nordic cross-disciplinary community of LA researchers, e.g. by hosting the Nordic LASI 2018 at Aalborg University and organizing Learning Analytics Research Symposium (LARS), which was held at University of Copenhagen in November 2018 (https://www.ind.ku.dk/lars2018)

2.3 Finland

Research on learning analytics started early in Finland with a focus on the social and collaborative aspects of learning. Tervakari and colleagues investigated the "TUT circle" which was an online social media enhanced learning platform at Tampere University of Technology. They reported on the utility of visualization of students' interactions, and researched the learning analytics potentials of the platform. The group later contributed with research on content analytics, social media analytics and teacher tools [33]. Other aspects of learning analytics followed such as predicting students' performance in programming courses and using machine learning methods to predict students' need for assistance [34]. A notable body of research comes from Järvelä and colleagues on self-regulated and collaborative learning, who investigated social shared regulation, interactions and engagement with collaborative learning and the temporal sequence of regulatory processes [35] [36]. The group are also working on multimodal physiological data as well as dispositional learning analytics [37] [38]. As the field is gaining recognition, many Finnish universities are now embracing the concept and research is increasingly reported from most Finnish universities.

Despite the development of techniques and methods to model and predict human learning, the field still lacks ability to connect the powers of learning sciences and learning analytics in effective way to understand the complexity of learning alone or together, reveal hidden human mental processes and model and trace trigger moments and critical patterns of learning processes [37]. The emerging need to combine the power of learning sciences and learning analytics is also recognized by Finish Science Academy, which funds high-quality scientific research and strengthens the position of science and research. For example, in spring 2019 Academy of Finland launched a project call "Digital Humanities" which reflects the emerging need to develop new methodologies. Especially Digital Humanities program emphasizes new ways to address novel methods and techniques in which digital technology and state-of-the-art computational science methods are used for collecting, managing and analyzing data in humanities and social sciences research as well as for modelling humanities and social science phenomena. Thus, the emphasis lies not only in collecting "big data", but also "small" (deep, rich) data, since so far, the potential of many overarching conceptual and methodological questions remain unexplored and under-theorized.

The large body of empirical and theoretical advances in the field of self-regulated learning (SRL) [37] has indisputable evidence that such skills improve learning with students of all ages. However, there has been much less understanding how learning analytics are grounded in the literature on self-regulated learning and how self-regulated learning is supported. This is much due the fact, that SRL processes (i.e. cognitive, metacognitive, motivational and emotional) are invisible for naked eye and therefore difficult to capture [37]. Fortunately, due the technological and methodological advancements in the field, there is potential to transform these mental processes at least to some extent in a visible form to provide learning analytics for teacher and students.

During the past years, there has been increasing interest to collect and analyze multimodal data (i.e. log data, physiological data, situated self-reports) to better capture the mental processes of human learning [37]. For example, [39] applied multimodal data (e.g. physiological data, facial expression data and video data) evidencing that it is possible to make situational characteristic involving to the regulated learning process visible. Facial expression recognition has potential to reveal valence of emotions during collaborative learning. Visible interactions recorded from the video data has potential to reveal type of interaction, but also instances when students engage for self-regulated learning.

2.4 Germany

In 2016, Ifenthaler and Schumacher [40] report that research on learning analytics in Germany is scarce and that there are only a few projects focusing on the implementation of learning analytics systems. In 2019, several research projects are being funded by the German Federal Ministry of Education and Research focusing on technology integration and analytics in educational organizations [41]. For example, the aim of the project 'Utilizing Learning Analytics for Study Success' is to conduct a systematic review and construct a set of policies for German higher education institutions to adopt learning analytics capabilities into their existing learning environments. Precisely, the goals of the project are a) first to build a systematic review of empirical evidence demonstrating how learning analytics have been successful in facilitating student success in continuation and completion of their university courses both nationally and internationally, and forming the basis for aim b) to make policy recommendations for the German higher education sector in order to accept and implement such systems within institutions.

It became evident from the integrative review that robust empirical findings on a large scale to support the effectiveness of learning analytics actually retaining students onto courses are still lacking [42]. Therefore, it is imperative to leverage existing learning theory, psychological methods and connecting them to advances of learning analytics research for designing (quasi-)experimental studies including theoretical frameworks and sound empirical methodologies. The project findings of the interview study indicate that more work on ethical and privacy guidelines supporting a wider adoption of learning analytics systems is needed [42] as well as work towards a standardized learning analytics system which can be integrated into any learning environment providing reliable at-risk student prediction, prevention and intervention strategies [43]. In particular, personalized learning environments are increasingly demanded and valued in education institutions to create a tailored learning package optimized for each individual learner based on their personal profile which could contain information such as their geo-social demographic backgrounds, their previous qualifications, how they engaged in the recruitment journey, their activities on social media and websites, as well as tracking information on their searches [44].

Additional findings document issues with organizational readiness (Ifenthaler, 2017). For example, a standard infrastructure of educational institutions includes a student management system, a learning management system and a course management system. However, these systems are deeply embedded into the organization's infrastructure and often are not designed to reveal data for analytics [45]. For accessing the necessary data, various connections to the organizations' legacy systems have to be established which are able to access the students' profiles, to capture the actual learning processes and get access to curricula data. As these legacy systems are often based on various technologies, each connection has to be implemented as an individual project which is labor and cost intensive. Besides the technological challenges, staff capabilities are also changing when implementing learning analytics systems. Not only new staff roles but also further development of existing staff is required for successful implementation of learning analytics systems [46].

2.5 Norway

Although the collection, interpretation, and visualization of multimodal data has been extremely challenging for researchers, recent technological developments and data science, and AI advancements have boosted the growth of non-invasive high-frequency multimodal-data collections.

Learners' traces are generated during their interaction with technologies, such interaction is often complex but offers opportunities for collecting rich and multimodal data [47] [48], MultiModal Learning Analytics (MMLA), as the literature refers to them. In order to unfold the benefits of MMLA, the Learner-Computer Interaction

(LCI) lab at the Norwegian University of Science and Technology (NTNU) focuses on overcoming the difficulties in gathering and making sense of MMLA. In other words, we attempt to identify, *how insights generated during learner-computer interaction help us to design future learning environments and improve the learning experience.*

For many years, the design of learning technologies has been utilizing click-streams and keystrokes as the primary data source for modelling and predicting learning behavior. In recent work at NTNU researchers set out to quantify what, if any, advantages do physiological sensing techniques provide for the design of learning technologies [47] in a lab context with 251 game sessions and 17 users focusing on skill development (i.e., user's ability to master complex tasks).

Furthermore, when dealing with data channels in multiple modes and modalities, a major issue lies in determining combinations of the multimodal data channels that are necessary for one to make valid and reliable inferences regarding the temporally unfolding learning processes, and selecting the algorithms and analytical tools to use. Recent research at NTNU has proposed a novel approach, called "grey-box" approach, that bridges the hypothesis/literature-driven (measurements/feature selection) "white-box" approach with the computation-driven (feature fusion) "black-box" approach [49]. The authors aimed to extend current methodological paradigms in understanding effortful behavior and learning performance in adaptive learning conditions with new, cutting-edge, interdisciplinary work on building pipelines for educational data, using innovative tools and techniques

Another research dimension explored at NTNU with regard to multimodal learning analytics is the modelling of learner behavior, by taking advantage of the inherent temporality in the physiological data. The Generalized Auto-Regressive Conditional Heteroskedasticity (GARCH) method was applied with learners' physiological time-series data to model their behavior, and make suggestions about how the models can be further utilized to provide proactive feedback to learners [49].

Moreover, investigating and explaining the patterns of learners' engagement in adaptive learning conditions is a core issue towards improving the quality of personalized learning services. The research group at NTNU bridged complexity theory with multimodal data in order to capture specific patterns of engagement that foretell and explain learners' level of performance on adaptive learning procedures [50].

In a different context, the joint collaboration between the Centre for the Science of Learning & Technology (SLATE) from University of Bergen in Norway and Erasmus University Rotterdam from the Netherlands gave birth to interesting research studies in MOOCs. The first one was on exploring self-regulated learning in Coursera platform by [51]. Wong et al [51] employed sequence pattern mining to identify self-regulated learning studying strategies to a group in MOOCs where student was offered self-reflection and monitoring intervention. One more contribution between SLATE and the Dutch university is a book chapter titled "*Educational Theories and Learning Analytics: From Data to Knowledge*" by [52]. The chapter aimed at discussing how learning theories and learning analytics are important components of educational research. In addition, the chapter suggests that more experimental studies are needed for applied learning analytics in general and in Europe more specifically.

In Norway as well, there has been research on ethical aspects of learning analytics. For instance [53] carried out a research study at the Open University in the United Kingdom in which they examined student's behavior in higher education and their attitudes to privacy. The authors plan to carry out the same research study in Norway next year together with South Africa. Furthermore, the study by [53] looked at the three levels of consent in MOOCs, micro, meso, and macro. Based on reviewing the policies of the biggest four MOOC providers, the paper proposes a need for greater transparency around the implications of users granting consent at the point of registration.

Another interesting project brought from Norway are those related to the medical and health sector. SLATE from the University of Bergen is involved in a consortium project called OERBioMed. Biomedicine seeks to explain physiological processes at the molecular and individual level. Such information is essential for the understanding of disease progression and for the development of new treatments and therapies. This current and future medical research relies on the existence of people with expertise in the biomedical field. To raise the quality of teaching, training and learning within the field of biomedicine, new and innovative approaches are required. To this end, this project deals with open-access and online courses to increase the bioethical knowledge and awareness in the biomedical community. SLATE is involved in this project by providing help and support to launch massive open online courses in collaboration with all the partners from the Nordic countries. SLATE also provide learning analytics and statistical services to the partners.

2.6 Spain

Data driven education has been a hot topic in Spain in the last 10 years. In fact, there are several relevant works in the field of Learning Analytics, Visual Analytics, Educational Data Mining, Multimodal Analytics, etc. However, there are some issues in the Spanish landscape related with Data Driven Education, issues that are also common in other countries. These are:

- Data driven education is a relatively new research field, and therefore the quantity and variety of topics of interest is high
- The current level of global or campus-wide application of learning analytics in companies and public and private organizations is low
- The fragmentation of research groups, and the difficulty they have to reuse and replicate research designs, results and outcomes of others
- The focus of disciplines such as learning analytics has been mostly technical and it is necessary a multidisciplinary perspective that involves also profiles such as educators, psychologist or sociologist
- It is also desirable to engage different organizations in the use of disciplines such as Learning Analytics (companies, public administrators, non-higher education institutions, etc.)

- The low number of professionals in this field, with the emergence of the new data scientists this is close to be solved, but it is still needed a very specific profile in the educational field
- The knowledge that research groups have about themselves, ongoing projects, institutions and organizations interested in Data Driven Education is limited.

In order address these problems and centralize the efforts carried out related to these topics SNOLA was defined. SNOLA (Spanish Network Of Learning Analytics, http://snola.es), informally created in 2013, emerges as a network composed of the main national researchers in the LA field, comprising 10 researchers from 9 Spanish Research Groups. SNOLA primarily has a technical approach, but it also integrates other educational visions and disciplines that give the network a wider scope. The main objectives of SNOLA are:

- The promotion of collaboration among the participants in the Network, as well as with other interested parties (companies and public and private educational institutions) and other European and international LA collaboration networks
- The diffusion and organization of LA initiatives at a national scale
- Making resources to effectively integrate LA in educational processes available to the public; and 4) provide researchers and professionals adequate training to face and give answer to the new challenges of Digital Society risen by the incorporation of ICT in education. From December of 2015 to June of 2018, SNOLA was granted by the Spanish Government as Thematic Network which help the network to support different events and activities.

At the same time that SNOLA was defined several projects have been developed with Spanish institutions related with Data Driven Education. Some are international projects (mostly European) such as: LACE Project (http://www.laceproject.eu/), SHEILA Project (https://sheilaproject.eu/), Make World (https://makeworld.eu), Go-Lab (https://www.golabz.eu/) or LALA Project (https://www.lalaproject.org/); some other are granted by the Spanish Government through national calls such as the projects EEE or RESET; or by Regional Governments such as eMadrid. These projects deal with different issues and in some of them Data Driven Education is the main topic and in other it is employed to support the results, processes or products developed. Some of topics explored could be the teamwork assessment, intelligent tutors that make suggestions depending on learning evidences or the use of Learning Analytics in CSCL.

Regarding the scientific events it should be noted that exist several relevant initiatives:

The Learning Analytics Summer Institute Spain, linked to the SOLAR intiative. It is a conference supported by SNOLA with several editions. First Spanish Edition was hold in 2013 at Granada (http://grinugr.org/noticias-de-eventos/lasi-spain/), 2014 at Madrid (http://lasimadrid2014.scc.uned.es/), 2015 (https://blogs.deusto.es/lasi2015Bilbao/) and 2016 (https://lasi16.snola.es/) at Bilbao, 2017 at Madrid (https://lasi17.snola.es/) and 2018 at León (https://lasi18.snola.es/). This year will take place in Vigo. It began as an event for discussion between researchers in the field of Learning Analytics and also as a contact point with experts. However now it includes also sessions with scientific papers presentations, networking sessions, companies' sessions, etc.

The Learning Analytics Track included in the TEEM Conference, an international scientific conference defined in Spain in 2013. The track is leaded by Spanish researchers but includes works from people all around the world. It began in 2013 and since then this track has taken place every year. During the track several scientific papers are briefly presented and discussed with experts. Some of this track editions have been associated to special issues in journals such as Computers in Human Behavior [2] or the International Journal of Engineering Education [3]. Several topics have been discussed during the track, some of the most significant could be: Prediction of students success or failure based in their learning and interaction evidences; tools to improve learning process, Learning Analytics and Mobile devices, Ethics about Learning Analytics, Visual Learning Analytics, Academic Analytics, Multimodal Learning Analytics, Social Network Analytics, Competence Assessment through Learning Analytics, Discussion about the quantity and quality of data to make decisions in educational contexts, Application of Learning Analytics tools and techniques, Personalization of Learning by using Learning Analytics, etc. More information about this track and the research woks included in it can be found here [54-59].

Other seminars such as LAIKA, SIIE 2016, WPLA at ECTEL, LATCEE (in Educon) were also leaded by Spanish research groups and deals with similar topics as the previous ones.

It should be noted that in conferences such as LASI – Spain companies were involved. In this way it was possible to know what were they doing about Learning Analytics and what they require from the academy. Companies such IBM, Euskaltel, Sun Edison, Brambles or Eticas Consulting participate in several LASI Conference and enrich the perspective about Data Driven Education in Spain.

2.7 Sweden

Even though the field of learning analytics is an evolving field of both research and practice [4], there have already been some relevant efforts in terms of its development in a Swedish context. These attempts are currently expanding in higher educational settings. For instance, a number of research directions have been explored with a learning analytics approach by a research group at Stockholm University, focusing on aspects such as problem-based learning [60], teacher education [61], collaborative learning [62], self-regulated behavior [63], prediction of student performance in blended learning and in flipped classroom settings [64], and prediction of performance and completion of master- and bachelor thesis [65].

Other examples of research conducted by Swedish researchers include the exploration of multimodal learning analytics [66], and prediction of students' mastery of skills [67].

The efforts in K-12 education are in particular relevant to an ongoing digitalization of the Swedish education system. One of the recent developments in this regard include: i) the Swedish government decision for digitalization of the schools, with a supplement that presents a national strategy for this (and ii) National action plan for digitization of the Swedish school system. Both of these documents highlight a need for a strategic and systematic data collection for increased opportunities for follow-up of the school system's digitalization, with the main purpose to increase the availability of comparable data that makes it possible to study the connection between methods and results. However, these endeavors are still in their infancy. Thus, the present report illustrates the state of the art that largely relates to adult and particularly, higher education.

We are only aware of one project at the K-12 level, which focused on 21st century skills and collaborative problem-solving of students in secondary school [68]. In this project, which was funded by Swedish Association of Local Authorities and Regions (SKL), researchers aimed to assess collaborative problem-solving skills in technology-enhanced environments. The project included students from five different schools in the Stockholm area. In this particular study, the researchers exploited multimodal data (video and log data) in order to identify and predict students collaborative problem-solving skills.

Swedish Educational Data*: Data-Driven Innovation for World Learning Education* is one of the recent development projects (with no particular educational level focused) that aims at establishing Swedish Educational Data as a support organization for data-driven innovation for education (2017-2019). The project is funded by Vinnova, Sweden's innovation agency and led by KTH Royal Institute of Technology. It includes both public and private actors from the education industry. They interact actively to increase data usage for education. This is important since fragmentation can cause each part to develop their own analytical methods and their own data management when they instead may be applicable across the entire field. The project's results will be released at the end of 2019.

In another recent research and development project funded by IFOUS (2017-2020), *Programming in school subjects* ("Programmering i ämnesundervisningen), which do not have an explicit focus on learning analytics, researchers are currently exploring how digital data generated in K-12 classrooms can be used to develop teaching practices and the identification of students computational thinking skills, based on preliminary findings reported in [69].

In general, albeit some research has been conducted in Sweden, so far learning analytics research has not been funded by the larger research agencies.

3 Discussion

Today, in the era of big data and analytics, researcher as well as educational stakeholders are calling for data-driven development of education. Consequently, aiming to capitalize on the rewarding applications of big data in different fields, researchers are hard at work building the field of data-driven education and research (through the field of learning analytics). In Europe, learning analytics has been embraced by researchers since the early days, contributions span all venues of research in the field, such as collaborative learning, visualization of learners' interactions, learning dashboards, dispositional learning analytics, self-regulated learning and multimodal learning analytics. Researchers have also explored all kinds of data from single course digital traces to large scale academic analytics. Efforts are increasingly organized to tackle new problems, establish collaborative research groups, set up learning analytics focused scientific events, and build capacity in the interdisciplinary field.

Lately, Some European projects have been launched, examples are the STELA project between KU Leuven, University of Nottingham, TU Delft and TU Graz (Leitner & Ebner, 2016), The LACE project (The Learning Analytics Community Exchange), SHEILA Project and the collaboration between (SLATE) at the University of Bergen and Erasmus University Rotterdam. Nonetheless, collaboration and funding on the European level are still relatively scarce. On the national level, funding of learning analytics projects is just taking off. In Austria, the ministry of education will support learning analytics research in the next years. In Denmark, The ATEL project was funded by Innovation Fund Denmark (Innovationsfonden) which will track the early stage literacy development through learning analytics. In Finland, the Finish Science Academy launched the project “Digital Humanities” to use data for analyzing and modelling humanities and social sciences. In Germany, the Federal Ministry of Education and Research have funded some projects such as ‘Utilizing Learning Analytics for Study Success’ (Mao et al., 2019). In Norway and Spain several projects are starting with the help of national funding agencies. However, in Sweden, the funded projects are still very few.

Taking together, the previous examples for funding are way behind the expected in a time where learning is in the center of public and political attention. Let alone the accelerating successes of using big data across many disciplines. The rich and diverse potentials of data-driven applications are reflected in the heterogeneous nature of reported research from different research groups. Although such diversity and breadth of applications have helped emphasize the worth of using data to improve education, it has also emphasized a need for organizing efforts. Fragmentation, division and paucity of collaborative projects seem to be prevailing. Nevertheless, a number of collaborative groups are emerging. Examples include The Learning Analytics research group at Stockholm University, The Danish Center for Big Data Analytics Driven Innovation (DABAI) and the Spanish Network of Learning Analytics. Relatedly, learning analytics scientific events have been organized, such as the Nordic-LASI.

As the field of learning analytics is relatively new, researchers around the world are working to tackle the emerging challenges, such as proving the value of using data-driven decision making, aligning the field with learning sciences, collecting useful data while securing the privacy and agency of learners. European researchers are no exception, they are facing the same challenges as well as their own challenges. most important is that the large interest and work of researchers and groups around Europe has not led to national adoption or European level strategies relative the ubiquitous adoption of technology in education. Most countries have not established national policies for learners’ data or guidelines that govern the ethical usage of data in research or education. We also conclude, that learning analytics research on pre-university level to high extent have been overlooked. In the same vein, learning analytics has not received enough focus form national and European national bodies. Such funding is necessary for taking steps towards data-driven development of education.

4 References

[1] Ferguson, R. (2012). Learning analytics: drivers, developments and challenges. *International Journal of Technology Enhanced Learning*, *4*(5/6), 304-317. https://doi.org/10.1504/ijtel.2012.051816

[2] Long, P. D., & Siemens, G. (2011). Penetrating the fog: Analytics in learning and education. *EDUCAUSE Review, 46*(5), 31–40.

[3] Ifenthaler, D., Mah, D.-K., & Yau, J. Y.-K. (2019). Utilising learning analytics for study success. Reflections on current empirical findings. In D. Ifenthaler, J. Y.-K. Yau, & D.-K. Mah (Eds.), *Utilizing learning analytics to support study success* (pp. 27–36). New York, NY: Springer. https://doi.org/10.1007/978-3-319-64792-0_2

[4] Viberg, O., Hatakka, M., Bälter, O., & Mavroudi, A. (2018). The current landscape of learning analytics in higher education. *Computers in Human Behavior*. https://doi.org/10.1016/j.chb.2018.07.027

[5] Papamitsiou, Z., & Economides, A. A. (2014). Learning analytics and educational data mining in practice: A systematic literature review of empirical evidence. *Journal of Educational Technology & Society*, *17*(4), 49-64.

[6] Ferguson, R., Brasher, A., Clow, D., Cooper, A., Hillaire, G., Mittelmeier, J., & Rienties, B. (2016). Research Evidence on the Use of Learning Analytics. *Tech. Rep.*

[7] ET2020 (2016). Learning Analytics – Key messages. report, European Commission. Available online at https://ec.europa.eu/education/sites/education/files/2016-pla-learning- analytics_en.pdf.

[8] Schön, M., Ebner, M., Kothmeier, G. (2012) It's Just About Learning the Multiplication Table, In Proceedings of the 2nd *International Conference on Learning Analytics and Knowledge (LAK '12*), Simon Buckingham Shum, Dragan Gasevic, and Rebecca Ferguson (Eds.). ACM, New York, NY, USA, 73-81. https://doi.org/10.1145/2330601.2330624

[9] Ebner, M., Schön, M. (2013) Why Learning Analytics in Primary Education Matters!,*Bulletin of the Technical Committee on Learning Technology*, Karagiannidis, C. & Graf, S (Ed.), Volume 15, Issue 2, April 2013, p. 14-17

[10] Taraghi, B., Ebner, M., Saranti, A., Schön, M. (2014) On Using Markov Chain to Evidence the Learning Structures and Difficulty Levels of One Digit Multiplication, In: *Proceedings of the Fourth International Conference on Learning Analytics And Knowledge*, ACM, New York, p. 68-72. https://doi.org/10.1145/2567574.2567614

[11] Kraja, E., Taraghi, B. & Ebner, M. (2017). The Multiplication Table as an innovative Learning Analytics Application. In J. Johnston (Ed.), *Proceedings of EdMedia: World Conference on Educational Media and Technology 2017* (pp. 810-820). Association for the Advancement of Computing in Education (AACE).

[12] Ebner, M., Schön, M., Neuhold, B. (2014). Learning Analytics in basic math education – first results from the field, *eLearning Papers*, 36, pp. 24-27

[13] Ebner, M. & Pronegg, M. (2015). Use of Learning Analytics Applications in Mathematics with Elementary Learners. *International Journal of Academic Research in Education*, 1(2), 26-39. https://doi.org/10.17985/ijare.37247

[14] Edtstadler, K., Ebner, M., Ebner, M. (2015) Improved German Spelling Acquisition through Learning Analytics. *eLearning Papers*, 45, pp. 17-28

[15] Khalil, M., Ebner, M. (2016). What is Learning Analytics about? A Survey of Different Methods Used in 2013-2015. *Conference proceeding of the 8th e-Learning Excellence Conference*, 2016. Dubai, UAE. pp. 294-304

[16] Khalil, M., Ebner, M. (2016) Clustering patterns of engagement in Massive Open Online Courses (MOOCs): the use of learning analytics to reveal student categories. *Journal of Computing in Higher Education*. Volume 29. pp. 114-132. https://doi.org/10.1007/s12528-016-9126-9

[17] Khalil, M. & Ebner, M. (2016). Learning Analytics in MOOCs: Can Data Improve Students Retention and Learning?. *In Proceedings of EdMedia: World Conference on Educational Media and Technology 2016* (pp. 569-576). Association for the Advancement of Computing in Education (AACE)

[18] Khalil, M., Ebner, M., & Admiraal, W. (2017). How can Gamification Improve MOOC Students Engagement?. In *proceedings of the European Conference on Game Based Learning*, Graz, Austria, (pp. 819-828)

[19] Ebner, M., Khalil, M., Schön, S., Gütl, C., Aschemann, B., Frei, W., Röthler, D. (2017) How Inverse Blended Learning Can Turn Up Learning with MOOCs? In: *Proceedings of the International Conference MOOC-MAKER 2017*. Antigua Guatemala, Guatemala, November 16-17, 2017, pp. 21-30

[20] De Laet, T, Broos, T.,van Staalduinen, J.-P., Leitner, P., Ebner, M. (2016) Successful transition from secondary to higher education using learning analytics. *44th SEFI Conference*, Tampere, Finland

[21] Leitner P., Ebner M. (2017) Development of a Dashboard for Learning Analytics in Higher Education. In: Zaphiris P., Ioannou A. (eds) Learning and Collabo- ration Technologies. *Technology in Education*. LCT 2017. Lecture Notes in Computer Science, vol 10296. pp. 293-301 Springer, Cham. https://doi.org/10.1007/978-3-319-58515-4_23

[22] Khalil, M. & Ebner, M. (2016d) De-Identification in Learning Analytics. *Journal of Learning Analytics*. 3(1). pp. 129 – 138. https://doi.org/10.18608/jla.2016.31.8

[23] Leitnerr P., Ebner M., Ebner M. (2019) Learning Analytics Challenges to Overcome in Higher Education Institutions. In: Ifenthaler D., Mah DK., Yau JK. (eds) *Utilizing Learning Analytics to Support Study Success.* Springer, Cham. https://doi.org/10.1007/978-3-319-64792-0_6

[24] Bruun, J., Ray, P. J., & Udby, L. (2019). Network analyses of student engagement with online textbook problems. *arXiv preprint arXiv:1903.11390*.

[25] Alstrup, S., Hansen, C., Hansen, C., Hjuler, N., Lorenzen, S., & Pham, N. (2017). DABAI: A data driven project for e-Learning in Denmark. In P. Peres, & A. Mesquita (Eds.), *ECEL17 - Proceedings of the 16th European Conference on e-Learning* (pp. 18-24). Academic Conferences and Publishing International.

[26] Beuchert, L., Humlum, M. K., Nielsen, H. S., & Smith, N. (2018). The short-term effects of school consolidation on student achievement: Evidence of disruption?. *Economics of Education Review*, *65*, 31-47. https://doi.org/10.1016/j.econedurev.2018.05.004

[27] Ringgaard, A. (2019, April 4). *Forskning baseret på nationale test kan være smittet med fejl*. Retrieved from https://videnskab.dk/kultur-samfund/forskning-baseret-paa-nationale-test-kan-vaere-smittet-med-fejl. https://doi.org/10.4220/sykepleienf.2008.0078

[28] Bundsgaard, J. & Kreiner S. (2019). *Undersøgelse af de nationale tests måleegenskaber*. 2nd edition. Copenhagen: Aarhus Universitet, Danmarks institut for Pædagogik og Uddannelse. Retrieved from: http://edu.au.dk/fileadmin/edu/Udgivelser/Rapporter/Ebog_-_Nationale_tests_maaleegenskaber.pdf . https://doi.org/10.7146/aul.319.217

[29] Spikol, D., Bruun, J., & Udby, L. Exploring Physics Education in the Classroom and the Laboratory with Multimodal Learning Analytics. *and provide timely personalised feedback*

to students (Page 10) 6. Khalil, M: The Unbearable Lightness of Consent: An Eye on Learning Analytics and MOOCs (Page 13) 7. Minard, M. S: Learning Analytics from a Student Perspective (Page 15), 21. https://doi.org/10.1145/2883851.2883920

[30] Udby, L., Jensen, P., Bruun, J., Willendrup, P., Schober, H., Neuhaus, J., . & Lefmann, K. (2013). E-learning neutron scattering. *Neutron News*, *24*(1), 18-23. https://doi.org/10.1080/10448632.2013.751795

[31] Overgaard, J. H., Bruun, J., May, M., & Udby, L. (2017). Virtual neutron scattering experiments-Training and preparing students for large-scale facility experiments. *Tidsskriftet Læring og Medier (LOM)*, *9*(16). https://doi.org/10.7146/lom.v9i16.24231

[32] Bruun, J., Ray, P. J., & Udby, L. (2019). Network analyses of student engagement with online textbook problems. *arXiv preprint arXiv:1903.11390*.

[33] Kuosa, K., Koro, J., Tervakari, A., Paukkeri, J., & Kailanto, M. (2014). Content analysis and visualizations: Tools for a social media-enhanced learning environment. In Proceedings of 2014 International Conference on Interactive Collaborative Learning, ICL 2014 (pp. 361–367). https://doi.org/10.1109/icl.2014.7017799

[34] Ahadi, A., Lister, R., Haapala, H., & Vihavainen, A. (2015). Exploring Machine Learning Methods to Automatically Identify Students in Need of Assistance (pp. 121–130). University of Technology, Sydney, Australia. https://doi.org/10.1145/2787622.2787717

[35] Järvelä, S., Järvenoja, H., Malmberg, J., Isohätälä, J., & Sobocinski, M. (2016). How do types of interaction and phases of self-regulated learning set a stage for collaborative engagement? Learning and Instruction, 43, 39–51. https://doi.org/10.1016/j.learninstruc.2016.01.005

[36] Järvelä, S., Kirschner, P. A., Panadero, E., Malmberg, J., Phielix, C., Jaspers, J., … Järvenoja, H. (2014). Enhancing socially shared regulation in collaborative learning groups: designing for CSCL regulation tools. Educational Technology Research and Development, 63(1), 125–142. https://doi.org/10.1007/s11423-014-9358-1

[37] Järvelä, S., Malmberg, J., Haataja, E., Sobocinski, M., & Kirschner, P. A. (2019). What multimodal data can tell us about the students' regulation of their learning process? Learning and Instruction. https://doi.org/10.1016/j.learninstruc.2019.04.004

[38] Järvenoja, H., Järvelä, S., Törmänen, T., Näykki, P., Malmberg, J., Kurki, K., … Isohätälä, J. (2018). Capturing motivation and emotion regulation during a learning process. Frontline Learning Research, 6(3), 85–104. https://doi.org/10.14786/flr.v6i3.369

[39] Malmberg, J., Järvelä, S., Holappa, J., Haataja, E., Huang, X., & Siipo, A. (2019). Going beyond what is visible: What multichannel data can reveal about interaction in the context of collaborative learning?. *Computers in Human Behavior*, *96*, 235-245. https://doi.org/10.1016/j.chb.2018.06.030

[40] Ifenthaler, D., & Schumacher, C. (2016a). Learning Analytics im Hochschulkontext. *WiSt - Wirtschaftswissenschaftliches Studium, 4*, 172–177. https://doi.org/10.15358/0340-1650-2016-4-176

[41] Mao, J., Ifenthaler, D., Fujimoto, T., Garavaglia, A., & Rossi, P. G. (2019). National policies and educational technology: a synopsis of trends and perspectives from five countries. *TechTrends, 63*(3), 284–293. https://doi.org/10.1007/s11528-019-00396-0

[42] Ifenthaler, D., & Schumacher, C. (2019). Releasing personal information within learning analytics systems. In D. G. Sampson, J. M. Spector, D. Ifenthaler, P. Isaias, & S. Sergis (Eds.), *Learning technologies for transforming teaching, learning and assessment at large scale* (pp. 3–18). New York, NY: Springer. https://doi.org/10.1007/978-3-030-15130-0_1

[43] Gašević, D., Dawson, S., Rogers, T., & Gašević, D. (2016). Learning analytics should not promote one size fits all: The effects of instructional conditions in predicting academic

success. *Internet and Higher Education, 28*, 68–84. https://doi.org/10.1016/j.iheduc.2015.10.002
[44] Schumacher, C., & Ifenthaler, D. (2018a). Features students really expect from learning analytics. *Computers in Human Behavior, 78*, 397–407. https://doi.org/10.1016/j.chb.2017.06.030
[45] Klasen, D., & Ifenthaler, D. (2019). Implementing learning analytics into existing higher education legacy systems. In D. Ifenthaler, J. Y.-K. Yau, & D.-K. Mah (Eds.), *Utilizing learning analytics to support study success* (pp. 61–72). New York, NY: Springer. https://doi.org/10.1007/978-3-319-64792-0_4
[46] Ifenthaler, D. (2017). Are higher education institutions prepared for learning analytics? *TechTrends, 61*(4), 366–371. https://doi.org/10.1007/s11528-016-0154-0
[47] Giannakos, M.N., Sharma, K., Pappas, I.O., Kostakos, V., Velloso, E. (2019). Multimodaldata as a means to understand the learning experience. International Journal ofInformation Management, 48, 108–119 https://doi.org/10.1016/j.ijinfomgt.2019.02.003
[48] Giannakos, M., Sharma, K., Martinez-Maldonado, R., Dillenbourg, P., & Rogers, Y. (2018). Learner-computer interaction. In Proceedings of the 10th Nordic Conference on Human-Computer Interaction (pp. 968-971). ACM. https://doi.org/10.1145/3240167.3240259
[49] Sharma, K., Papamitsiou, Z., Giannakos, M.N. (2019). Building Pipelines for EducationalData: Using AI and Multimodal Analytics to Explain Learning in Adaptive Self-Assessment. British Journal of Educational Technology (to appear)
[50] Papamitsiou, Z., Pappas, I.O., Sharma, K., Giannakos, M.N. (2019). Utilizing multimodaldata through an fsQCA approach to explain engagement in adaptive learning. IEEE Transactions on Learning Technology (to appear)
[51] Wong, J., Khalil, M., Baars, M., de Koning, B. B., & Paas, F. (2019a). Exploring sequences of learner activities in relation to self-regulated learning in a massive open online course. *Computers & Education*, 103595. https://doi.org/10.1016/j.compedu.2019.103595
[52] Wong, J., Baars, M., de Koning, B. B., van der Zee, T., Davis, D., Khalil, M., . & Paas, F. (2019b). Educational Theories and Learning Analytics: From Data to Knowledge. In *Utilizing Learning Analytics to Support Study Success* (pp. 3-25). Springer, Cham. https://doi.org/10.1007/978-3-319-64792-0_1
[53] Slade, S., Prinsloo, P., & Khalil, M. (2019). Learning analytics at the intersections of student trust, disclosure and benefit. In Proceedings of the 9th International Conference on Learning Analytics & Knowledge (pp. 235-244). ACM. https://doi.org/10.1145/3303772.3303796
[54] Hernández-García, Á., and Conde, M.Á.: 'Learning analytics: The good, the bad (and the ugly)'. Proc. of the 6th International Conference on Technological Ecosystems for Enhancing Multiculturality, Salamanca, Spain2018, pp. 290-293. https://doi.org/10.1145/3284179.3284229
[55] Conde, M.Á., and Hernández-García, Á.: 'Learning analytics: Expanding the frontier'. Proc. of the 5th International Conference on Technological Ecosystems for Enhancing Multiculturality, Cádiz, Spain2017 pp. 1-5. https://doi.org/10.1145/3144826.3145386
[56] Hernández-García, Á., and Conde, M.Á.: 'Learning analytics: needs and opportunities'. Proc. of the 4th International Conference on Technological Ecosystems for Enhancing Multiculturality, Salamanca, Spain, 2016, pp.309-312. https://doi.org/10.1145/3012430.3012533
[57] Conde, M.Á., Hernández-García, Á., and Oliveira, A.: 'Endless horizons?: addressing current concerns about learning analytics'. Proc. of the 3rd International Conference on

Technological Ecosystems for Enhancing Multiculturality, Porto, Portugal, 2015, pp. 259-262. https://doi.org/10.1145/2808580.2808619

[58] Hernández-García, Á., and Conde-González, M.Á.: 'Dealing with complexity: educational data and tools for learning analytics'. Proc. of the 2nd International Conference on Technological Ecosystems for Enhancing Multiculturality, Salamanca, Spain, 2014, pp. 263-268. https://doi.org/10.1145/2669711.2669909

[59] Conde, M.A., and Hernández-García, A.: 'A promised land for educational decision-making?: present and future of learning analytics'. Proc. of the 1st International Conference on Technological Ecosystem for Enhancing Multiculturality, Salamanca, Spain, 2013 pp. 239-243. https://doi.org/10.1145/2536536.2536573

[60] Saqr, M., Fors, U., Nouri, J. (2018). Using Social Network Analysis to Understand Online Problem Based Learning and Predict Performance. PLoS One. https://doi.org/10.1371/journal.pone.0203590

[61] Karunaratne T., and Byungura J. (2017). Using log data of virtual learning environments to examine the effectiveness of online learning for teacher education in Rwanda, In Proceedings of the 2017 International conference IST-Africa, 31 May – 02 June 2017, Windhoek, Namibia. https://doi.org/10.23919/istafrica.2017.8102410

[62] Saqr, M., Fors, U., Tedre, M. & Nouri, J. (2018b). How Social Network Analysis Can Be Used to Monitor Online Collaborative Learning and Guide an Informed Intervention. PLoS One. https://doi.org/10.1371/journal.pone.0194777

[63] Saqr, M., Nouri, J. Fors, U. (2018). Time to focus on the temporal dimension of learning. A learning analytics study of the temporal patterns of students' interactions and self-regulation. International Journal of Technology Enhanced Learning. https://doi.org/10.1504/ijtel.2019.10020597

[64] Nouri, J., Saqr, M & Fors, U. (2019a). Predicting performance of students in a flipped classroom using machine learning: towards automated data-driven formative feedback. 10th International Conference on Education, Training and Informatics (ICETI 2019).

[65] Nouri, J., Larsson, K., & Saqr, M. (2019). Identifying factors for master thesis completion and non-completion through learning analytics and machine learning. In proceeding of 14th European Conference on Technology Enhanced Learning (EC-TEL).

[66] Spikol, D., Bruun, J., & Udby, L. Exploring Physics Education in the Classroom and the Laboratory with Multimodal Learning Analytics and provide timely personalised feedback to students. LASI 2018.

[67] Bälter, O., Zimmaro, D., & Thille, C. (2018). Estimating the minimum number of opportunities needed for all students to achieve predicted mastery. *Smart Learning Environments*, *5*(1), 15. https://doi.org/10.1186/s40561-018-0064-z

[68] Nouri, J. Åkerfeldt, A., Fors, U., Selander, S. (2017). Assessing collaborative problem solving skills in technology-enhanced learning environments – the PISA framework and modes of communication. International Journal of Emerging Technologies in Learning. [S.l.], v. 12, n. 04, p. pp. 163-174. https://doi.org/10.3991/ijet.v12i04.6737

[69] Nouri, J., Zhang, L., Mannila, L.& Norén, E. (2019). Development of computational thinking, digital competence and 21st century skills when learning programming in K-9. Education Inquiry. https://doi.org/10.1080/20004508.2019.1627844

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