

MASTER'S THESIS

Adopting Learning Analytics in Dutch Education

What are adoption challenges and how to overcome them

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Adopting Learning Analytics in Dutch Education

What are adoption challenges and how to overcome them

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Abstract

Educational organizations in the Netherlands only adopt (Learning) Analytics on a small scale, limited to local initiatives. In this research the focus lies on discovering the challenges of implementing Learning Analytics in the higher educational sector in the Netherlands. Within this research multiple challenges and their solutions are identified. The existing literature already showed four key challenges: Stakeholder engagement, weak pedagogical grounding, resources and ethics & privacy. To search for solutions, the domain of Business Analytics provided a different perspective. Business Analytics exists for a longer period of time and is considered more mature in comparison to Learning Analytics. The more mature state of BA provided useful insights how certain challenges were solved and what challenges lie ahead when LA matures. The findings from the semi-structured interviews confirmed the identified challenges from the literature, and provided a new challenge and some new solutions. The findings show that the Dutch Higher Education have their own unique set of challenges to overcome. These challenges and solutions differ for each educational organization within their own context. This research aims to provide an overview for all identified challenges paired with solutions to overcome adoption challenges and to utilize LA at scale within the Netherlands.

Keywords

Learning Analytics
Adoption challenges
Solutions
Dutch Higher Education Institutions
Business Analytics

Summary

Learning Analytics is, together with Academic Analytics and Educational data mining, one of the three analytical domains focused on the educational sector. Within LA, the focus lies on improvement of education, monitoring learning progression for both teacher and learner. A lot of literature is already available about LA. However, this is limited to geographical areas of North America, the United Kingdom, and Australia. LA exists within the Netherlands, yet not much literature is available about LA in the Netherlands. For what is known, LA in the Netherlands is only used on a small scale, limited to local initiatives. It isn't used on a larger scale, like in the case of Business Analytics. BA is in a more mature state in comparison than LA. BA could provide answers to (future) challenges that exist within LA. It raises the question why LA isn't used at scale within the Netherlands, even though plenty of literature is available. To discover what Dutch Higher Educational Institutes (HEI) holds back to adopt Learning Analytics, challenges and possible solutions must be identified. By identifying the challenges and possible solutions adoption challenges can be overcome, growing LA to become a prominent asset within Dutch Higher Education.

The literature of LA slightly differs from BA. BA added Data Governance: Data Quality as an independent challenge. Because of BA two challenges are renamed. The literature of both LA and BA fused together identified organizational culture, weak pedagogical grounding, resources and data governance as challenges for successful adoption of LA. Regarding the research methodology, semi-structured interviews were used with a sample of twelve respondents, eight from LA and four from BA. The analysis of the transcriptions showed there was a confirmation of the challenges as identified in the literature. There was a new challenge identified: communication. Within this challenge there is a lack of clarity where LA is used for, no clear communication about LA-initiatives, unable to find the person (single point of contact) or department who are accountable within implementation and scaling of LA initiatives for retrieving information. Resources was mentioned the most as a challenge, closely followed by data governance, with comes organizational culture, communication and weak pedagogical grounding coming after, in that order.

When combining the literature with the findings, the challenges that hold back the adoption within the Netherlands are: (1) organizational culture, (2) weak pedagogical grounding, (3) resources, (4) Data Governance and (5) Communication. The findings also propose solutions: A fixed point of contact; Clear goals that are in line with the vision strategy; Clearly identify the needs; Create independence: with training and empower workers for independent decision making; Demonstrate value by showing results; Getting the right people at the table; Good documentation of governance; Hiring (external) staff; and user friendly, look & feel. The solutions provide content to formulate implications for practice. The most frequently mentioned solution was to demonstrate value by showing results. This intended to improve the pedagogical grounding within LA. Resources was mentioned the most as a challenge, and therefore try to lower workload and provide employees with training to gain more data knowledge within organizations. When implementing new software think of user friendliness, look and feel and try to involve the right people. Also think of a data governance document providing information about First data governance in general: clear goals, flow of approval, documentation: providing manuals and guidelines, second data quality: availability, completeness and accessibility. Third data privacy and security: ethical dilemmas, privacy and security dilemmas regarding GDPR, confidentiality and compliance. Within communication is about finding clear communication lines, keep all the stakeholders in mind and try to involve them. Try to centralize communication through a single point of contact for LA initiatives to know where to find necessary information. The research confirms that LA challenges are the same in the Netherlands as other geographical areas, yet LA didn't discuss Data Quality nor describes how to get to a data informed culture. **This** are implications for further research.

Index

ABSTRACT	2
KEYWORDS	2
SUMMARY	3
1. INTRODUCTION.....	6
1.1 INTRODUCTION TO ANALYTICS.....	6
1.2 RELEVANCE OF CONDUCTING RESEARCH ABOUT LEARNING ANALYTICS	7
1.3 CHALLENGES WITHIN LEARNING ANALYTICS	7
1.4 READING GUIDE.....	8
2. THEORETICAL FRAMEWORK.....	9
2.1 IDENTIFICATION OF RELEVANT LITERATURE	9
2.2 ORGANIZING THE LITERATURE	9
2.3 CODING AND ANALYSIS.....	9
2.4 PRESENTATION OF FINDINGS	10
2.4.1 WHAT ARE CHALLENGES THAT WITHHOLD HEI FROM IMPLEMENTING LEARNING ANALYTICS?	10
2.4.2 WHAT ARE THE CHALLENGES WITH SIMILAR IMPLEMENTATION OF ANALYTICS AT SCALE IN BUSINESS ANALYTICS?	12
2.4.3 WHAT ARE WAYS TO OVERCOME THE IDENTIFIED CHALLENGES?	14
3. METHODOLOGY	17
3.1 RESEARCH METHOD	17
3.2 ELABORATION OF THE METHOD.....	17
3.3 DATA ANALYSIS.....	17
3.4 VALIDITY, RELIABILITY AND ETHICAL ASPECTS.....	18
4. RESULTS	20
4.1 DATA COLLECTION AND ANALYSIS.....	20
4.2 CHALLENGES MENTIONED IN INTERVIEWS	20
4.2.1 CHALLENGES MENTIONED IN LEARNING ANALYTICS	20
4.2.2 CHALLENGES MENTIONED IN BUSINESS ANALYTICS	21
4.3 COMPARISON BETWEEN LA AND BA.....	22
4.4 SOLUTIONS MENTIONED IN INTERVIEWS.....	23
5. DISCUSSIONS, CONCLUSIONS AND RECOMMENDATIONS	25
5.1 DISCUSSIONS.....	25
5.1.1 WHAT ARE CHALLENGES THAT WITHHOLD HEI FROM IMPLEMENTING LEARNING ANALYTICS?	25
5.1.2 WHAT ARE CHALLENGES WITH SIMILAR IMPLEMENTATION OF ANALYTICS AT SCALE IN BUSINESS ANALYTICS?.....	25
5.1.3 WHAT ARE WAYS TO OVERCOME THE IDENTIFIED CHALLENGES?	26

5.2 CONCLUSIONS	26
5.3 RECOMMENDATIONS FOR PRACTICE	26
5.4 RECOMMENDATIONS FOR FURTHER RESEARCH	27
6. REFERENCES	28
7. APPENDIX.....	34
APPENDIX 1: CHALLENGES LA WITHIN THE LITERATURE.....	34
APPENDIX 2: CHALLENGES BA WITHIN THE LITERATURE	35
APPENDIX 3: SOLUTIONS TO THE CHALLENGES WITHIN THE LITERATURE	36
APPENDIX 4: INTERVIEW QUESTIONS REGARDING LA/ BA.....	38

1. Introduction

1.1 Introduction to Analytics

Big Data is everywhere, at every place. Think of supermarkets with their best-selling or highest profit products, the local factory that keeps an eye on the production rate or a shop that wants to keep track of costs. It all started on a small scale, but nowadays Data Analytics are becoming more and more important (J. Zakir et al, 2015). Many new studies arise to describe and interpret ‘analytics’ in their own way (Romero, C., & Ventura, S., 2020). There are many types of analytics. The most common known appellation is Big Data Analytics, which can be described as *the process of gathering, processing and turning huge amounts of unstructured data into useful information for providing insights and support decision making* (H.J. Watson, 2014). As analytics emerged, it quickly won a reputation as a useful way to enhance business performance and market share (Zahir et al., 2005). Data Analytics also set foot in the educational sector. Many variations of Data Analytics originated in the educational sector, which can be summarized in three central domains: Academic Analytics, Educational Data Mining (EDM) and Learning Analytics (LA) (Romero, C., & Ventura, S., 2020). Each of these analytics serves their purpose in their own way. The focus of Academic Analytics (AA) lies in the supporting sector of business intelligence with emphasis on institutional, regional, and even international level (Long & Siemens, 2011). Educational Data Mining (EDM) has its focus on developing automated tools for data mining, which is computer focused. By using EDM organization try to discover certain patterns or knowledge hidden in data (Abu Saa, Amjad, 2016). Learning Analytics focuses on the actual quality of the learning process as an individual (Siemens & Baker, 2012). There are different ways to define Learning Analytics. Ifenthaler (2015) defines Learning Analytics as *“The use, assessment, elicitation and analysis of static and dynamic information about learners and learning environments, for the near real-time modeling, prediction and optimization of learning processes, and learning environments, as well as for educational decision-making”*. LAK (2011) defines LA as *“The measurement, collection, analysis, and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs”* and Duval (2012) definition reads *“Learning Analytics is about collecting traces that learners leave behind and using those traces to improve learning”*. As could be concluded: Learning Analytics focuses on improving the quality of education, it describes multiple ways to improve learning in the educational setting which leads to the creation of an optimal learning environment. Within this research the focus lies on improving the quality of education with the support of analytics. Figure 1 shows the different areas of focus within EDM and LA. EDM and AA don’t fit because of the computer-oriented approach and focus on macro level, where this research focusses on organizational level. Learning Analytics is considered the best fit within the context of this research, LA focusses on organizational level and its interaction between statistics and education.

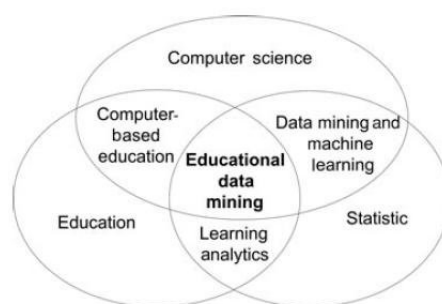


Figure 1: Focus of Educational Data Mining vs Learning Analytics (Hashim, Ali & Khalaf, Alaa & Akeel, Wid, 2018).

To apply Learning Analytics at Higher Education institutions, awareness has to be developed. Ferguson (2012) stated that digitalization enhanced the importance and relevance of digital learning. This development together with the Corona pandemic in 2019, which led to obligatory digital working and learning, became a temporary new standard with a turnaround in the way of thinking and educating as a result (Kniffin et al, 2020). Combining the development of LA with the Coronavirus lockdown, learning data became more available than ever before. This data provided institutions more valuable insights, making them realize the importance and value of Learning Analytics (Ferguson, 2012).

1.2 Relevance of conducting research about Learning Analytics

LA provides a new dimension to education. Some of the possibilities with LA as an extension to physical class: Good overview and new useful insights, better decision making, tailored education because of insights of student metrics and performance, all meant to provide better education for students. Things can be monitored and controlled with much more ease for both the teacher and the student within this mix of digital and physical context. Also, some insights (such as passiveness or uncertainty etc.) would never be so clear and measurable in the hybrid context in comparison to the physical class only. The environment provided the learners and teachers a hybrid setting (both physical and digital) in which both parties were able to perform better, which in the end improves the quality of the education.

There is a lot of literature available about different geographical areas regarding LA, such as North America, the United Kingdom, and Australia (Ferguson & Clow, 2017; Yau & Ifenthaler, 2020), but only a limited number of articles regarding LA address the Netherlands (SURF, 2015; Knobbout & Van der Stappen, 2020, SURF, 2021 (non-scientific); Knobbout, 2021). Because of the limited literature available in the Netherlands, it is not fully clear how LA performs in The Netherlands. Many organizations are willing to use Learning Analytics as a way to enhance quality of education, but few organizations actually use these on a bigger scale. Only small initiatives are being used, while the possibilities are much more (SURF, 2021 non-scientific; Knobbout, 2021). There are opportunities to improve quality of education, ready to be expanded. The non-scientific article of SURF/Surf Community (2021) shows that out of the 50 respondents only 8 are not using LA at this moment, while all the other 42 respondents try to implement LA, mostly limited to local initiatives. It proves the willingness of stakeholders to using Learning Analytics, yet don't manage to scale these initiatives. What is holding Dutch Higher Education back to take LA to the next level within the Netherlands? This research aims to identify the challenges and possible explanations to overcome adoption challenges of Learning Analytics within the Netherlands. The challenges of LA could exist within more mature domains of analytics, such as Business Analytics (BA). BA could provide insights about unidentified challenges or possible answers to challenges that aren't identified yet within the domain of Learning Analytics. Furthermore, in the Netherlands other challenges could exist in comparison to the other geographical areas.

1.3 Challenges within Learning Analytics

Even though the benefits and value of LA is recognized, before using LA, several challenges have to be dealt with. These challenges are versatile and are mainly complex in nature. Several scientists have done research in identifying these challenges. In order to overcome these challenges and implement LA in the right way, a collection of challenges was identified, accompanied with possible solutions (Greller & Drachslar, 2012, 2016; Tsai et al., 2018, 2019, 2020; Ferguson et al., 2014, 2016, 2019; Tsai & Gasevic, 2017; Gasevic et al., 2019). There is plenty of knowledge and literature available for adoption of Learning Analytics, yet this knowledge about LA is mostly focused on North America, the United Kingdom, and Australia (Ferguson & Clow, 2017; Yau & Ifenthaler, 2020). There are many advantages for the utilization of LA, however, LA aren't adopted as much as it was expected (Drachslar et al., 2014). So, what is holding HE (Higher Educations) back in adopting LA? Even though there are many theoretical frameworks and plenty of knowledge about Learning Analytics, there are few Dutch Higher Education (HE) instances that have adopted Learning Analytics (Tsai, 2020). This leads to the following main research question:

For what reasons do Dutch Higher Educational Institutions (HEI) not systematically adopt Learning Analytics at scale?

The answer to this question gives insights as to why Dutch Higher Education are hesitant in systematically adopting Learning Analytics. Most of the Dutch Higher Educations only use LA within small projects and initiatives, but when used at scale (the acknowledged right to exist, as a prominent part of an organization) LA will mature and fulfil its full potential. The explanations will remove barriers in overcoming the challenges for successfully adopting Learning Analytics.

To answer the main question, we can decompose the main question into three sub-questions:

1. *What are the challenges that withhold HEI from implementing Learning Analytics?*

Which challenges are already identified, which new challenges might emerge within the adoption of Learning Analytics. It shows what Dutch Higher Education encounters when trying to successfully adopt Learning Analytics.

2. *What are the challenges with similar implementation of Analytics at scale in Business Analytics?* Business Analytics (BA) may be in a more mature state in comparison to LA. This domain could provide new insights in (un)identified challenges and solutions for current and future LA. The challenges and possible explanations of BA will be examined.

3. *What are ways to overcome the identified challenges?*

By addressing solutions to the discovered challenges, barriers will be removed. Resulting in possible explanations for the challenges. It enables organizations whenever they identify their unique set of challenges, there is a unique set of possible solutions to answer these challenges. It lowers the reticence for using LA at scale.

1.4 Reading Guide

This paper is structured into the following sections: literature review, research methodology, results, discussion, conclusion, implications, and limitations of the study.

The literature review (chapter two) will explain how the literature will be retrieved. There will be a set of considerations as to why an article will be assumed appropriate for selection. The abundance of relevant literature exposes the knowledge gap with regard to the problem statement.

The research methodology (chapter three) provides an overview of the planning how to conduct the research while maintaining reliability and validity. The selection of cases, the method of data gathering and the methods for coding will be explained. At the results (chapter four) the findings from the data will be exhibited with visualizations and will be provided with corresponding analysis. At the discussion (chapter five) the findings will be compared to the existing literature from chapter two, the most notable similarities and differences will be presented in the conclusions. From the conclusions the implications for practice will be offered. After the implications for practice the limitations of the paper will be reviewed.

2. Theoretical framework

In chapter two the theoretical relevance will be outlined. There will be a description of how the articles were selected: under which conditions an article was selected, where the articles were found and why they were selected, supporting the problem statement and exposing the knowledge gap. The literature review was executed according to the method of Bandara et al. (2015). This method comprises four phases: Identification of relevant literature, organization of analysis, coding and analysis and last the presentation of findings.

2.1 Identification of relevant literature

In this section the justification of the selected papers will be discussed. To start looking in the right area, Romero & Ventura (2020) provides the top related journals that are relevant for research in the Learning Analytics domain (see table 1). This will be the foundation for further investigation of the relevant articles. The databases that were consulted were the databases of SAGE Journals Online, Scienedirect (Elsevier) and Taylor & Francis Online because the large databases (200.000+ hits). Within these databases a filter was used to find the journals of table 1 until each journal didn't provide new articles. To find more relevant literature articles, snowballing was applied from the articles that were found and selected. The total selection of all articles is listed in table 2.

Table 1: Available journals for Learning Analytics
From JCR Social Science Edition 2019 (Romero & Ventura, 2020)

Journal Title	Number of papers
Journal of Learning Analytics	143
Computers and Education	81
British Journal of Educational Technology	65
Journal of Educational Data Mining	48
Journal of Artificial Intelligence in Education	47
IEEE Transactions on Learning Technologies	33
Journal of Computer Assisted Learning	32
International Journal on Technology Enhanced Learning	31
User Modelling and User-Adopted Interaction	27
Internet and Higher Education	26
Computer Applications in Engineering Education	26

Within the databases keywords were used to find relevant articles. The following keywords were entered as requirements of selection:

'Learning Analytics' AND ('Frameworks' OR 'Adoption' OR 'Implementation' OR 'Integration' OR 'Challenges' OR 'Barriers' OR 'at scale').

And for the other domains, so called Business Analytics:

'Business Analytics' AND ('Adoption Challenges' OR 'Implementation Challenges').

The results within the journals showed many articles, but in order to determine which articles were considered as being relevant, the abstract of every article was read. The requirement to select an article consists of a hit on the combination of keywords which is provided within the 'abstract' of an article.

2.2 Organizing the literature

According to Bandara et al. (2015), the second section consists of organizing the literature. These are put into the table 2 according to APA standards and put into chronological order per dimension.

2.3 Coding and Analysis

At the third section (Bandara, 2015), the literature needs to be coded. As already highlighted in the organization of analysis, table 2 is listed according to APA guidelines, combined with ranking by year and subject. The subject can be traced back to the keywords being used for the justification and selection of the articles in paragraph 2.1.

2.4 Presentation of findings

In the following chapter the findings will be presented and furtherly elaborated. When looking into the literature, multiple keywords were used to find articles. The four dimensions as shown in table 2 are the articles that were selected, extracted from the search and selection from the databases of paragraph 2.1. The findings show a first glimpse of the possible explanations on the research questions. Both the challenges and solutions will be paired with preliminary conclusions withdrawn from these findings. Table 2 below represents a sum of all identified articles, divided according to their keyword, included with LA (Learning Analytics) and BA (Business Analytics). Including BA is to strengthen the theoretical foundation and offer possible interesting insights of other domains discussing these same challenges. The articles from BA are highlighted with a red color.

Table 2: Dimensions of addressing LA frameworks and challenges

Note that some papers used more than one method, and thus they are classified for more than one dimension. The same definitions were used for finding the literature in chapter 2.1. Business Analytics articles are made cursive within this table.

Dimensions of LA articles	References
Adoption	Graham et al, 2013; Ferguson et al., 2014; Mirriahi et al., 2015; Arroway et al., 2016; Rubel & Jones, 2016; Colvin et al., 2017; Koul, Sahil, & Eydgahi, 2017; Wilson et al., 2017; Tsai et al., 2018; Dawson et al., 2018; Dollinger et al., 2019; Gasevic et al., 2019; Hilliger et al., 2019; Tsai, Whitelock-Wainwright, Gasevic, 2019; Tsai, Kovanović, Gasevic, 2019;
Challenges	Slade & Prinsloo, 2013; Ben Daniel, 2014; Elouazizi, 2014; Ferguson et al., 2014; Monroy et al., 2014; Macfadyen et al., 2014; SURF, 2015; Arroway et al., 2016; Baker, 2016; Drachler & Greller, 2016; Ferguson et al., 2016; Rubel & Jones, 2016; Colvin et al., 2017; Tsai & Gasevic, 2017; Ramanathan et al., 2017; Vidgen, Richard and Shaw, S. and Grant, D.G., 2017; M Attaran, S Attaran, 2018; Dursun Delen & Sudha Ram, 2018; Ferguson, 2019; Tsai et al., 2019; Maktadir et al., 2019; Knight, S., Gibson, A., & Shibani, A., 2020; Tsai et al., 2020; Ogbuke, Yusuf, Dharma & Mercango, 2020; Fernandez, V., & Gallardo-Gallardo, E., 2020; Kumar, et al, 2020; Kaliisa, Kluge & Mørch, 2021; Viberg & Grönlund, 2021; Raut, Surendra Yadav, Cheikhrouhou, Narwane & Narkhede, 2021;
Frameworks	Greller & Drachler, 2012; Bichsel, 2012; Norris & Baer, 2013; Siemens et al., 2013; Arnold et al., 2014; Colvin et al., 2016; Cormack, 2016; Oster et al., 2016; West et al., 2016; Steiner et al., 2016; Rodríguez-Triana et al., 2016; Vidgen, Richard and Shaw, S. and Grant, D.G., 2017; Martinez-Maldonado et al., 2017; Muslim et al., 2018; Liu et al, 2018; Sanagustin et al., 2019; Tsai et al., 2019; Omar et al., 2019; Law & Liang, 2020; Broos et al., 2020;
Implementation	Graham et al, 2013; Buerck, 2014; Herodotou, Rienties, Verdin & Boroowa, 2019; Rehrey et al., 2019; Ferguson et al., 2019; Pietro et al., 2019; Herodotou, Rienties, Hlosta, Boroowa, Mangafa, Zdrahal, 2020

2.4.1 What are challenges that withhold HEI from implementing Learning Analytics?

Most of the articles provide insights about the challenges when trying to implement LA. Findings show that LA articles consist of similar challenges, but the terminology and definitions of these challenges are used and explained differently: Privacy and ethics in one article can mean exactly the same while it may be called Data Governance in another article. To keep the terminology the same as much as possible the literature will be addressed as challenges (including barriers, hiccups) and solutions (including problem-solving, overcoming, recommendations, best practice, opportunities, implications).

Tsai et al. (2018; 2020) have executed research on implementation issues within the Learning Analytics domain and worked with multiple authors in the field of LA, such as Sanagustin (2020), Gasevic (2017, 2019, 2020), Dawson (2019) and Drachler (2020). The articles of Tsai show the complexity of research in the field of LA: every case is unique and offers a wide variety of challenges, versatile in their nature, but overall challenges can be categorized. In a detailed and often cited article, Tsai et al. (2020) identify four key challenges. These challenges are 1) stakeholder engagement and buy-in, 2) weak pedagogical grounding, 3) resources and 4) ethics and privacy.

Stakeholder engagement and buy-in

Most things that happen within this challenge are of behavioral nature. This challenge focuses on the culture within an organization. It is about understanding the norms and values of the organization, aiming to fulfil the mutual vision. It means that within the company, from top to bottom, the necessity needs to be clear for change and development. The acceptance for change starts with a right open mindset. Besides, a shared vision on the utilization of LA must exist (Tsai & Gasevic, 2017). To make a change in culture it is important to empower and encourage employees to make independent decisions. It creates accountability and engagement in the universal use of LA. Staying in the comfort

zone for too long can be a show stopper for new innovations. Just like very tall hierarchical companies which might slow the process of decision making (bureaucracy).

Weak pedagogical grounding

Within challenge two, there is a mismatch between pedagogical practice and educational theories. When implementing LA, organizations were not able to translate theories into practical relevance. It highlights the shortage of knowledge about LA. Without the knowledge what LA is and how to use it. People do not recognize the value of LA. Some initiatives are about LA while people are not aware of it. The shortage of overall knowledge makes it difficult for key stakeholders to have in-depth conversations about LA, resulting in LA not fulfilling its full potential (Gasevic et al., 2019). The aim of this challenge is to better match pedagogical practice and educational theories to meet the need of teacher and learner and to better measure learning progression.

Resources

The third challenge relates to the resource demand. This challenge relates to the resources that need to be provided for the adoption of LA. The resources can be divided into three categories: technical, assets and human. Technical: To make data understandable and accessible, (technological) investments must be made (Arroway et al., 2016). Investments can be considered as building a relational database for putting data logically together. Assets: Think of time and money. The FTE (fulltime equivalent) can determine the workload per FTE (time available per person). If an organization is considered understaffed for X reason (training, sick, holiday), probably the same workload will be divided under the same FTE, meaning an increase in workload. Human: organizations need to have plenty of people and they need to have the right skillset to work with LA.

Ethics and Privacy

The last challenge is about the ethics and privacy. In order to understand privacy and ethical challenges and their meaning better, the following definitions are withdrawn from the literature. Ethical, or 'Ethics' in this context, can be defined as 'the philosophy of morality that involves systematizing, defending, and recommending concepts of right and wrong conduct. In that sense, ethics is rather different from privacy' (Drachsler & Greller, 2016). It can be summarized to doing right or wrong, the good and the bad. Privacy is the continuous negotiation of boundaries of personal freedom and the ability to be secluded (Ferguson et al, 2016; Drachsler & Greller, 2016). The ethics and privacy are most often documented within guidelines and agreements and monitored with regard to compliancy.

These four dimensions are used for classification when identifying challenges and solutions at the methodology in chapter three. No other challenges were identified within LA literature. All of the LA articles redirect to the same dimensions of challenges. This led to the design of figure 2, which shows the classification of the authors of the LA literature and classified in all four identified overall challenges, divided into timeboxes of three years.

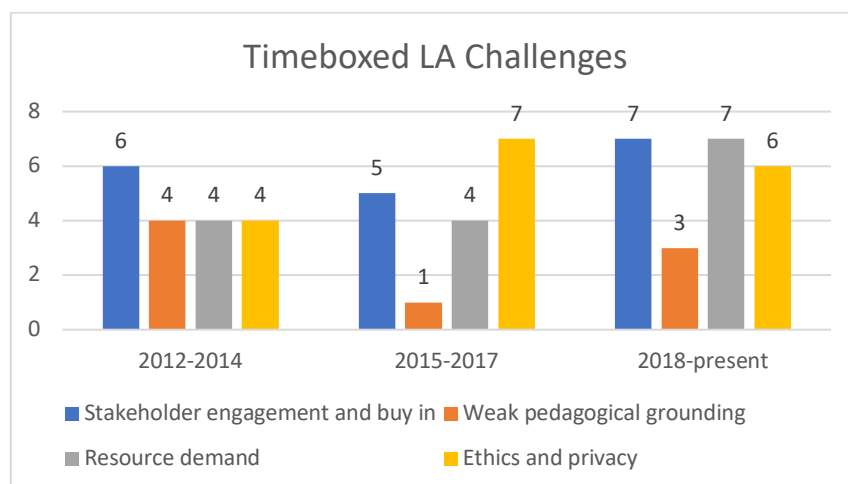


Figure 2: Timeboxed LA challenges

In the early years (2012-2014) most of the focus on the challenges was quite evenly distributed. Not many articles were available (six articles in total), which implicates that there wasn't a lot of knowledge about challenges regarding LA. In the second timebox (2015-2017), the focus of the articles started shifting. Less emphasis was on the 'weak pedagogical grounding' and more emphasis was on the 'ethics and privacy'. This shifting of focus possibly came along with the rise of awareness with privacy issues regarding social media and stricter standards for GDPR (sharing personal data within companies and people) around 2015. More LA articles became available after 2018- present (ten articles in total), meaning that the potential about LA was recognized. At the recent years (2018-present) the focus stayed the same. The 'weak pedagogical grounding' was being addressed a little more, but still the least. It implies that this challenge is discovered less or is considered not as important than the other challenges. The challenge 'resource demand' is one of the most addressed challenges and therefore is considered very important. While challenges may increase insecurity and doubts, other challenges may even reinforce that doubt. All these intertwined challenges withhold organizations in embracing LA, holding back to use LA at scale. As identified before, BA may provide new insights. Within BA, the actual focus lies within solving business problems within organizations with the utilization (large amounts) of data, mostly focused on production rates or turnover. It is a different domain that shows a lot of similarities with Learning Analytics (Barneveld, Arnold & Campbell, 2012). Within BA the same timebox of three years is made.

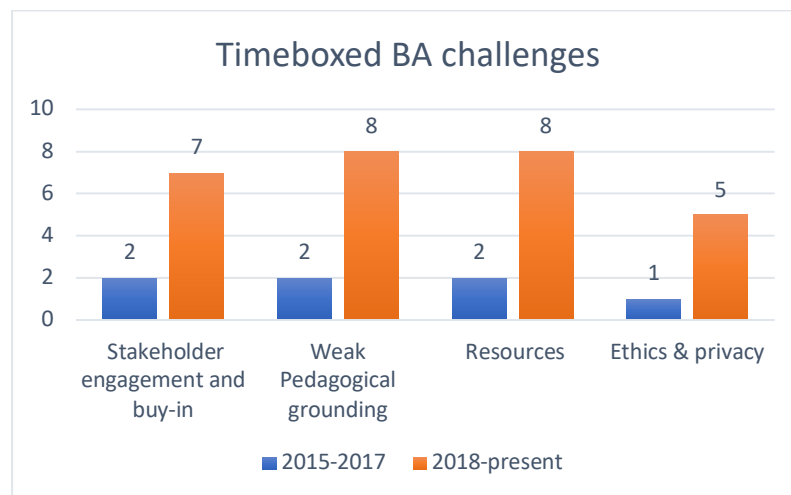


Figure 3: Timeboxed BA challenges

Compared to LA, the BA domain shows more recent articles (2015 – present), paired with a complete overview of the challenges. BA illustrates a more holistic approach; almost all challenges are being addressed. It suggests that BA have different ways of identifying similar problems, making it interesting to collect information about BA with regard to the challenges faced. Furthermore, it may be an indication that BA offers solutions for utilizing LA at scale. Within BA there is a lot of emphasis about control and use of data, which not fit within the four identified challenges within the literature of LA. In the next paragraph this will be further elaborated. The references of BA can be found in appendix 2, highlighted with a specific color and called other domains.

2.4.2 What are the challenges with similar implementation of Analytics at scale in Business Analytics?

BA implies to be in a more mature state within analytics; a lot of companies work with BA nowadays. Probably because there are a lot of examples proving the value of BA (Liu et al, 2018; Omar et al. 2019). Organizations adopt Business Analytics, reinforcing this statement. Value in this sense is recognizing the advantages that come along with the use of BA. Within BA, three overall divisions exist, descriptive, predictive and prescriptive (Fernandez, V., & Gallardo-Gallardo, E. (2020)). BA implementation literature address the TOE Framework (Tornatzky and Fleisher, 1990; Ramanathan et al. 2017; Omar et al, 2019; Kumar et al, 2020). The framework is easily applied and tailored to different sectors, proving its value till this day. It could be considered useful for educational purposes. 'TOE' can be divided in Technology, Organizational and Environmental context. Within Technology, the readiness and characteristics of that technology is being examined. Comparable to the resources challenge of LA. The Organizational context is comparable with the challenge stakeholder engagement

and buy-in. The definition of Organizational (culture) is considered a better way for naming the challenge stakeholder engagement and buy-in. The Environmental Context focusses on external factors such as regulations, data privacy and cybersecurity, comparable to the ethics, GDPR, Privacy and Security within LA. Yet the definition Data Governance is used. Governance can be defined as to what decisions must be made to ensure effective management and use of IT and who makes the decisions (Khatri, V. & Brown, C. V., 2010b). Data Governance consists of multiple domains: data quality, data security, data architecture, data lifecycle, meta data and data storage and infrastructure (Abraham et al, 2019). It is considered a better overall header for the ethics and privacy challenge of LA. To fuse LA and BA together, it would consist of data quality, data security, data privacy and ethics.

Other literature addressing BA challenges consist of similar key challenges: Value, people, technology, data, process, organization leadership (Vidgen, Richard and Shaw, S. and Grant, D.G., 2017; Fernandez, V., & Gallardo-Gallardo, E., 2020). Yet Fernandez, V., & Gallardo-Gallardo, E. (2020) discusses an interesting challenge that wasn't named explicit so far. Within Data and Models Fernandez, V., & Gallardo-Gallardo address data quality (DQ). They name DQ critical for success. Data quality (DQ) consist of different dimensions. According to Strong et al. (1997); Pipino et al. (2002) it consists of 4 categories: Intrinsic, Accessibility, Contextual and Representational. "Intrinsic is about the accuracy, objectivity, believability, reputation, accessibility covers accessibility, access security contextual addresses relevancy, value-added, timeliness, completeness, amount of data and last representational is about interpretability, ease of understanding, concise representation, consistent representation." It shows that DQ impacts on how to deal with Data Governance and the potential success when implementing BA. It is an element of Data Governance, but important enough to state explicitly. In short, in comparison to LA there are two other challenges that were named more explicit in BA that weren't that obvious in LA. Combining BA and LA challenges the challenge stakeholder engagement and buy-in is renamed to organizational culture and the challenge ethics, privacy and security of LA is renamed to Data Governance. The challenges are listed in table 3.

Table 3: Challenges identified from both LA and BA

The key challenges	Examples
Organizational Culture	<ul style="list-style-type: none"> - Norms and values within organizations, based on feelings, beliefs and personal interpretation. - Bureaucracy, slow decision making may delay implementations, making organizations less adaptive to change. - Acceptance to change, some people dislike change and would rather stick to their comfort zone. This behavior makes it difficult to innovate.
Weak pedagogical grounding	<ul style="list-style-type: none"> - Educational theory and pragmatic practice mismatch, the lack of knowledge for turning learning theories into pragmatic practices within LA - Unrecognized LA value, divergent definitions for LA exist. People don't know how to use LA. LA cannot be recognized nor thrive in circumstances where people don't know what LA is, means, and how to use it.
Resources	<ul style="list-style-type: none"> - In technical context, which hard and software do you have at disposal, their compatibility and ease of use - In assets, a shortage of time, money and in FTE to do the work. - In humans, a lack of people with the right skillset to perform the data-oriented work (on internal or external base).
Data Governance	<ul style="list-style-type: none"> - Data Governance (in general), documenting under what regulations and policies you are able to gather, store, process and dispose the data. - Data quality, availability, completeness and accessibility of data. - Data security, data privacy and ethics, about ethical dilemmas; compliance to policies and regulations, privacy; what can we process and store (anonymous, confidential, GDPR) and security; if is it stored safely.

2.4.3 What are ways to overcome the identified challenges?

Most of the articles addressing challenges also provide solutions to implement Learning Analytics. Because the solutions are written with regard to the challenges, the solutions were able to be put into the same four categories as the challenges. Yet, because there are more solutions than challenges, multiple solutions were addressed within these four dimensions. When recommendations (or a similar definition of addressing possible solutions) were being mentioned in an article, it was placed under the challenge it fits best. Detailed information about the classification of the solutions can be found in appendix 3. The following paragraph explain the different solutions belonging to their challenge.

Stakeholder engagement and buy-in (Tsai, 2020) / Organizational Culture

Supporting and empowering the key stakeholders, which in the end can mean a switch in organizational culture. For example, empowering stakeholders means giving stakeholders the confidence and ability to make decisions, which leads to more autonomy and thus, better decision making. Next to empowering key stakeholders, another solution is to distribute power structures for learning analytics data governance, making different people responsible, and thus, key stakeholders for the information in the right way. For example: Not making a HR-manager responsible for the security of data.

Weak pedagogical grounding

One of the addressed solutions is to start on a small scale, letting an institute to get used to the new technique without getting too big and complicated at the start. Let it start small and expand it, showing the practical relevance and value of it. Second, to enable stakeholders to understand and interpret data through training or interest and affinity with Analytics. This extends to: Look at the specific needs of the teachers and learners. In this way the data will be better understandable. One solution that has been addressed less often, is shared understanding of the levels of learning analytics data governance maturity. Most of the people aren't aware what LA is and what that entails. But to do so, mutual understanding must be created in the institution to bring Learning Analytics to the next level with regard to maturity. The last identified solution within this challenge is the continuous evaluation and re-assessment of the data outcomes. It focuses on growth along the development and utilization of LA data (in relation between teacher and learner) and to manage expectations.

Resources

Resources consist of two possible solutions. The focus lies on the investments into the available time and money. The first one is to make strategic investments technological hard- and software that supports data usage within LA. The second one is the labor capacity alias FTE. Invest in having enough people that have the right skillset to work with LA.

Ethics and privacy (Tsai, 2020) / Data Governance

The last challenge focusses on control of data (DQ), conflict management and power struggle. Try to provide clear manuals and guidelines to handle exceptions and maintain compliance, ethical use of data and avoid power struggle. The ethical and legal requirements need to be clear to everyone (transparency), especially for the people that are working with sensitive information such as GDPR requirements for example. Also, students have the right to withdraw or delete their personal data that is being used. Figure 4 provides an overview of the mentioned solutions per challenge.

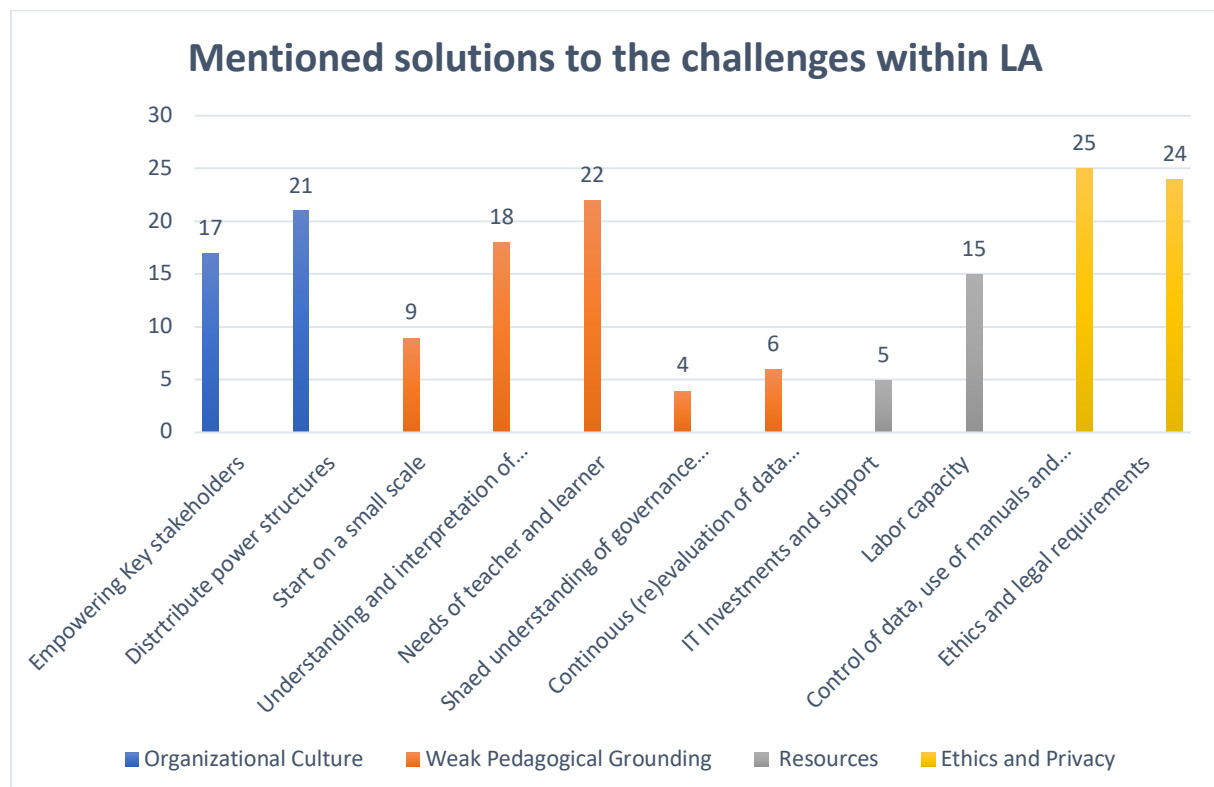


Figure 4: Solutions to the challenges within LA (extracted from 25 articles)

Figure 4 shows that solution shared understanding governance maturity, continuous (re)-evaluation of data outcomes and IT investments and support were mentioned the least. This could be explained with the limited articles available about pedagogical grounding, where the aim is to recognize, understand and connect educational theory to the pragmatic practice. This suggests that the knowledge of the technical integration and support is a difficult issue. A lot of (investments in) expertise is expected to

make hardware and software suitable for integrating LA. Most solutions are available for control of data, conflict management and power struggle and ethical and legal requirements, probably because this got the most media attention and is a well-known subject. Some of the authors were very specific on a challenge and the possible solution, such as Rubel & Jones (2016) and Ferguson et al. (2016) which aimed specifically on the privacy and ethics of data usage, Tsai (2019) focusses on leadership. Where other writers were quite general (Pietro, 2019; Knight, 2020).

Business Analytics articles show a wide variety of comparable solutions, therefore use the TOE-Framework as a guideline (Tornatzky and Fleisher, 1990). The most common solutions that both LA and BA literature indicate: Embrace and be open to (culture) change. It takes time and effort to get familiar to a new way of working, including the social interactions. Start setting up a strategy, this will help focus when setting goals for implementation of LA and at the same time not losing eye of the bigger picture. Take time and invest in IT and HR resources. Start at a small scale, keep risk low, and think of connecting theory and practice. Get everyone aboard, get the right people to the table, empower the right people and provide power structures. Think of correct data governance and keep in mind about the ethics, privacy and security. This will be further examined in the following chapters.

3. Methodology

Chapter three explains how the research will be executed. As described in the previous chapter, there is no explanation as to why Dutch Higher Education doesn't use LA at scale, even though a wide variety of challenges and proposed solutions are identified. Still, most of the research was geographically performed in Nord-America and Australia, which cannot be compared to the geographical area of the Netherlands. There is a possibility that the Dutch Education encounter some different challenges than the abovementioned studies. The specific target audience will be further explained in 3.2 Elaboration of the method.

3.1 Research method

The research will be conducted with semi-structured interviews. When trying not to deviate of the original subject, the semi-structured interviews will provide guidance. Semi-structured interviews still enable to go in depth when appropriate. This research aims to be explanatory because of the nature of the questions that need to be answered: Why? And How? (Yin, 2009) In relation to the research questions, why do things withhold successful adoption and how to solve these challenges? The aim of the interviews is to identify challenges and to put them on the test (theoretical replication). This data gathering will be performed until saturation of the results appear.

3.2 Elaboration of the method

Within this chapter the focus is on how the research will be executed. The case within the context of this research consists of two subdivisions: LA and BA. Within LA focus lies on the Dutch Higher Educational Institutes (HEI), which are the Universities of Applied Sciences and Universities. Within the Business Analytics the focus lies on the actual business-oriented organizations like Randstad, Shell, Governments etc. The interviews will be focused on two representatives with a different level of LA perspective. The different levels provide insights from different perspectives. For reliability purposes there will be interviews with at least six different organizations, consisting of four HEI institutions and two organizations with Business Analytics (BA). It means that twelve people will be interviewed in total (Saunders, M., Lewis, P. and Thornhill, A., 2012), respectively eight for LA and four for BA. Appointments with respondents will be made through e-mail to plan an interview. In appendix 4 the interview questions with the respondents are listed, enriched with questions from The SHEILA Framework (Tsai et al., 2018). Appointments will be scheduled with a time duration of an hour. To provide flexibility the interviews will take place online. The interview questions will be evaluated after every interview, because of the new insights. New questions are added whenever they possibly provide answers to the research question. The added questions are documented throughout the interviews and are included in appendix 4. The interviews consist of approximately 45 minutes in total. The interviews will be put into transcript. When the transcription is ready, it is suitable for analysis. In paragraph 3,4 the validity, reliability and ethics are further elaborated.

3.3 Data analysis

When the data is gathered and the transcriptions are made, the analysis will start. First the data needs to be cleaned from transcription errors. When transcriptions are ready, Doody, Slevin & Taggart (2012) suggest six steps within the coding process; (1) generating rich data, (2) familiarizing yourself with the data, (3) writing memo's, (4) indexing, (5) formation of themes and mapping and interpretation. The first step is to execute the interviews, generating the rich data. The questions can possibly be rephrased because of new insights. This can be recognized as familiarization with the data. After taking the interviews, the coding starts. With the help of memo's, the transcriptions will be ready for analysis. With the support of Atlas.ti (version 22), the transcriptions are coded in a systematical way. Krueger and Casey (2000) describe multiple steps to create consistency within the coding process. Requirement within the coding process is to have only one code for every question (and their context). When reading the transcriptions questions and their answers may be repetitive, which may result in quality loss of the coding. All transcriptions will be read and coded according to the predefined set of codes, which are listed in table 4.

Table 4: Predefined set of codes

The key challenges	Solutions
Organizational Culture	<ul style="list-style-type: none"> - Empowering Key Stakeholders - Divide power structures
Weak pedagogical grounding	<ul style="list-style-type: none"> - Start on a small scale - Understanding and interpreting the data - Look at the needs of teacher and learner - Shared understanding of governance maturity - Continuous re-evaluation of data outcomes
Resources	<ul style="list-style-type: none"> - Labor capacity - IT investments
Data Governance	<ul style="list-style-type: none"> - Control of data, use of manuals and guidelines - Ethical and legal requirements

The coding process alias indexing will be performed individually by two peers in order to increase the validity. There is a discussion between the peers about the identified codes, leading to one redefined set of identified codes. This is referred as the “formation of themes”. After updating the transcriptions with the latest codes, a frequency table of the mentioned challenges will be extracted from Atlas. After this, the mapping and interpretation of the data starts, with a separation between LA and BA. The (theoretical) knowledge available about LA and BA can be called ‘a priori’. In order to evaluate the current four categories and find possible new ones, axial coding will be used. Figure 5 illustrates the process of axial coding: from separate quotes to grouping these quotes. After axial coding the results are ready for (relational) analysis.

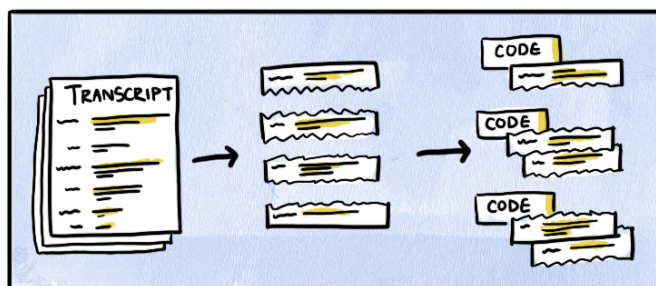


Figure 5: Process of axial coding

Out of these categories and relationships between them, a possible explanation can be found as to why Dutch Higher Education doesn't use Learning Analytics at scale yet. The business can provide a different view on similar challenges and possible solutions. In both cases there is the possibility that new categories of challenges might arise.

3.4 Validity, reliability and ethical aspects

3.4.1 Internal validity

As earlier highlighted in the elaboration of the method using semi-structured interviews, a couple of things were kept in mind when looking at the internal validity. When getting in contact with the respondents they will receive a mail which describes the purpose of the research. When understood and willing to co-operate, the respondents will have two different roles, one on executing level and one on an organizational level. It provides different perspectives and insights, from different angles, on (desired) use of LA/ BA within institutions. The cases are considered heterogenous, the respondents will be of different organizations and in different roles, meaning the background knowledge, abilities and interest differ for each respondent. The questions that were used were based on the questions of the SHEILA Framework (Tsai et al., 2018). It provided guidance to formulate the correct questions to measure what was intended to measure.

3.4.2 External validity

To get the right sample in terms of generalizability within the Netherlands, Saunders, M., Lewis, P. and Thornhill, A. (2012) describes a minimum of twelve interviews to be sufficient. More could be possible, but it must be feasible within the timespan of the research. Yet this research is limited to Dutch Higher Education., the research could be generalized to other different level learning within the Netherlands (primary education, secondary education, secondary vocational education).

3.4.3 Reliability

The interviews will take place in a digital setting. The respondents are asked for an appropriate time. The interviews will be planned as much as possible during working hours in the afternoon around 14:00 to 16:00. The combination of the digital setting and an appropriate time for the respondent, should make it as optimal as possible. When cancelled a new appointment will be made to make sure people are in a good mood and setting to give an interview. The coding of the interviews was performed independently by two peers to increase the reliability.

3.4.4 Ethical

The respondents that are approached must be open to co-operate. The information that was provided during the interviews will be handled with care. Before the interviews start, permission will be asked for recording, making it easier to make transcriptions. If a respondent will decline the request for recording, it will be noted down during the interview and will be sent to the interviewee for verification. If willing to co-operate, there will be told that the recordings will be deleted after the transcription is done and that the information used will be anonymized. It not only is an ethical thing to do, it also provides reliability; the recordings are rewindable, which makes the transcriptions of high quality.

4. Results

Within chapter four the results of the interviews will be shown. Chapter four is divided in four different headers. First, the way the interviews were conducted is being explained. The second header is about the challenges that were identified in the interviews. The third header talks about the comparison between LA and BA domains. The last one is about the mentioned solutions.

4.1 Data collection and analysis

The interviews were divided in BA and LA respondents. The interviews went as planned, average duration of the interviews was 35-45 minutes. After each interview, the questions were iteratively refined when necessary. Saturation on challenges and solutions appeared after taken 3/4th of all interviews. Transcriptions were made from the interviews and were coded. The challenges resources and data governance showed fixed recurring themes as identified in the literature, which were not used in the coding list. By dividing the two challenges into sub challenges the codes were more specific. Identifying the challenge resources doesn't mean an organization automatically finds problems with technical aspects, it could be a shortage of assets. Within Organizational Culture there was too much diversity of mentioned challenges to bring together into fixed themes. During the coding data governance is split in three sub challenges, which are DG (in general), DG Data Quality and DG Privacy & Security. For resources it is split into: Assets, humans and technical. One new challenge emerged from the data: Communication. This challenge is described in detail in paragraph 4.2.2.

4.2 Challenges mentioned in interviews

During the interviews all kind of challenges were mentioned. To create overview figure 5 and figure 6 show the mentioned challenges during these interviews, divided in BA and LA respondents.

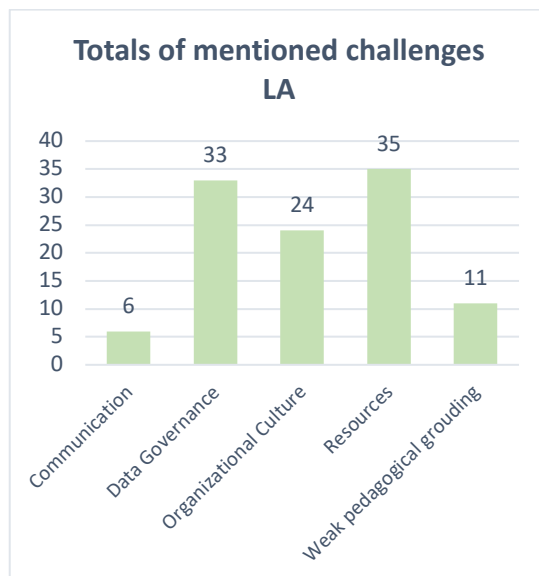


Figure 6: Totals of mentioned challenges LA

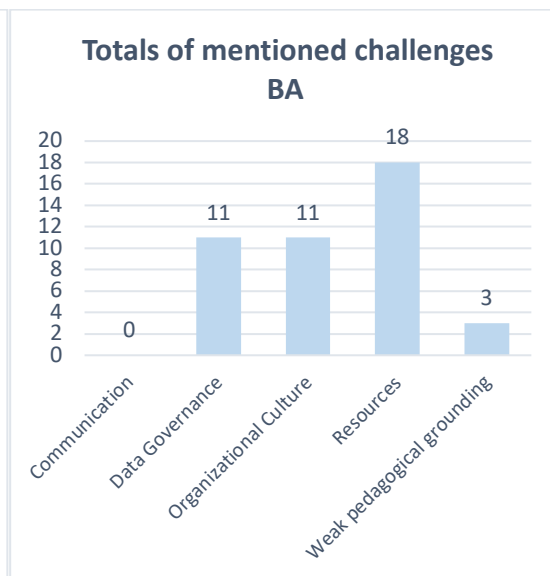


Figure 7: Totals of mentioned challenges BA

Both LA and BA contain a lot of similarities. The biggest difference is that BA only contained four respondents, where LA had eight respondents. Both figures indicate challenges that are quite the same. Both BA and LA will be further elaborated in the following paragraphs.

4.2.1 Challenges mentioned in Learning Analytics

Within LA, 'resources' is the most often identified challenge closely followed by 'Data Governance'. After that comes Organizational Culture, followed by weak pedagogical grounding and communication. As stated before, the challenges data governance and resources are split into sub challenges. This is visualized in figure 8.

During the interviews, people mostly mentioned the challenges already known from literature. Quotes of respondents confirm the statements: Organizational Culture not accepting for change: *‘People would like to stick to the things that work and don’t want to change that (ULA2).’*

However, coding shows one challenge that does not fit the a-priori codes. This relates to *communication*. Interviewees mention the lack of clarity where LA is used for, no clear communication about LA-initiatives, unable to find the person (single point of contact) or department who is accountable within implementation and scaling of LA initiatives for retrieving information. Answers confirm this statement. When being asked: “Did you feel involved when implementing this software?” the interviewee answered: *“no not really. There were things filled in and made up for me. You have to do with the means available to you (ULA4).’* Another interviewee that answered the same question: *“I think that it was at IT-party before where the IT-department was the driving force to get this done. From the business site, let’s say the education, was too much absent I suppose (ULA1)”*. Solving the communication challenge provides context and clarity between people and departments: Getting the right people at the table, clearly identifying specific needs, managing expectations which consists of a single point of contact, which can be an organization or person. As BBA1 told: *“there needs to be a project leader who possesses the skill to have good helicopter view and who is skilled multidisciplinary.”* Sometimes people are doing their own thing, not knowing people are already working on it or even made it before: *“That I think, it is not totally what I am doing, but it is stupid that I get in contact with you while the project is done for ¾th (ULA1).”*

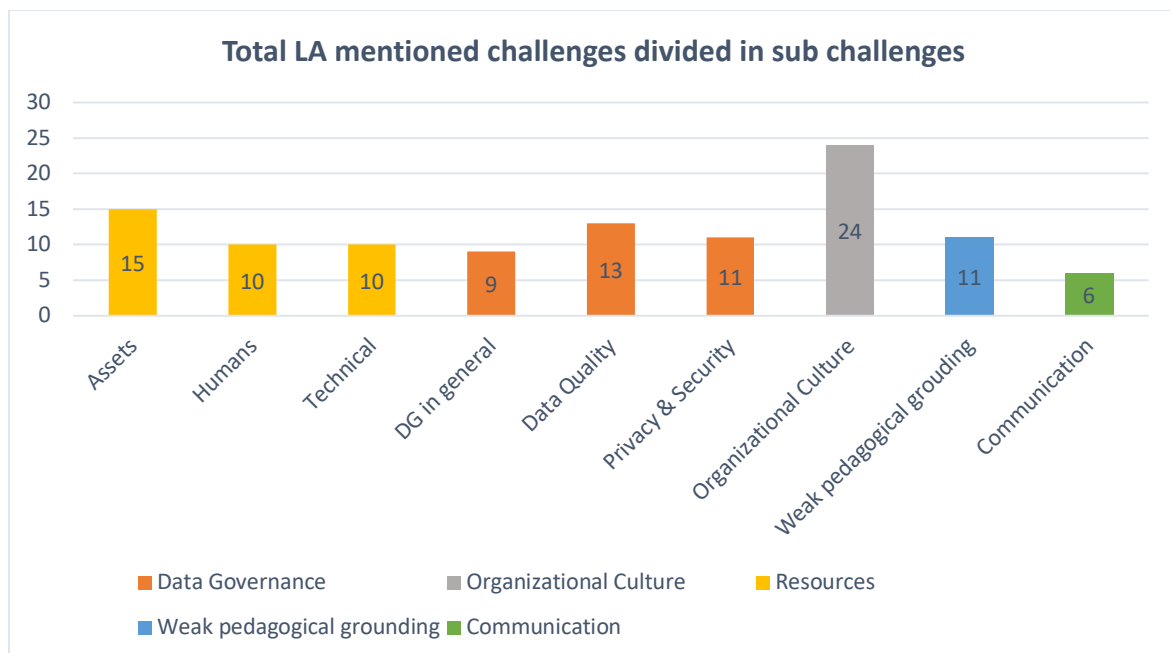


Figure 8: Total LA mentioned challenges divided in sub challenges (eight respondents)

4.2.2 Challenges mentioned in Business Analytics

When looking at figure 6, the results show that resources, just with LA, is mentioned the most. Figure 9 shows the distinguished (sub) challenges. Organizational Culture was mentioned eleven times. The challenge weak pedagogical grounding wasn’t named that often. It could be explained by the recognized value and more mature state of BA. The challenge communication was not mentioned by the respondents, which is remarkably. Supposedly communication was interpret as closely related or intertwined with the Organizational Culture, As BLA4 stated: *“you have to involve people. One of the first things security told us is to be open and transparent. Tell what you’re doing, why you’re doing it and with what purpose, why is it necessary and most important; how to help them with it.”*

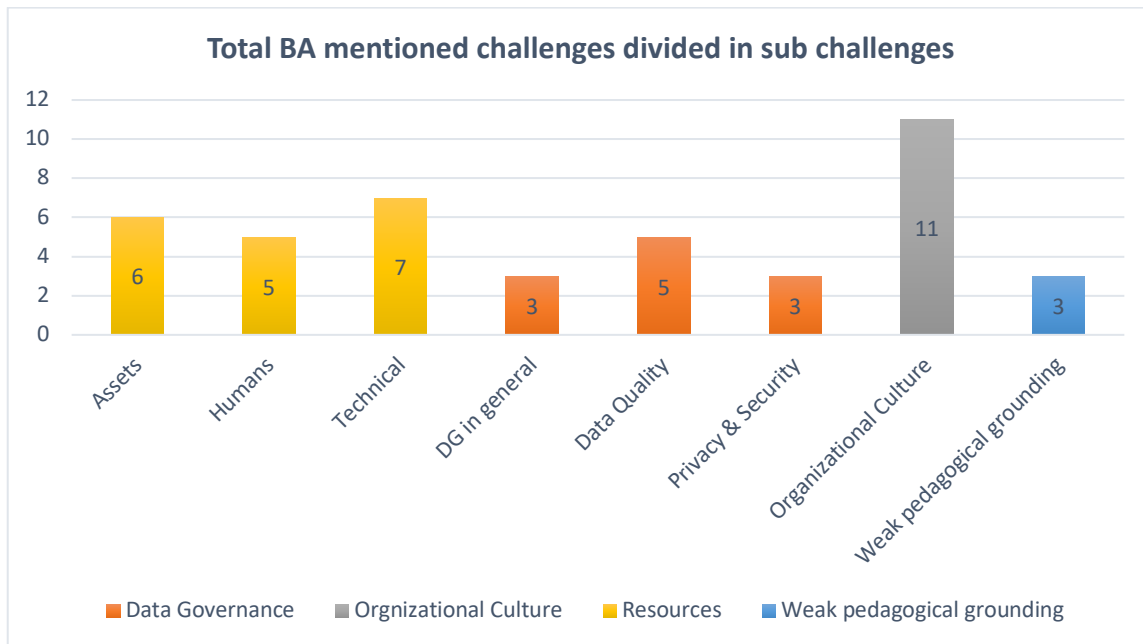


Figure 9: Total BA mentioned challenges divided in sub challenges (four respondents)

4.3 Comparison between LA and BA

When comparing BA to LA, the context of comparing has to be made equal. There were eight respondents for LA and four for BA, which makes comparing uneven. To solve this a relative table was used. The relative table shows the mentioned challenges within all interviews, divided into percentages and split into BA and LA.

Table 6: Differences in addressed Challenges in relative percentage between LA and BA

Challenges	Totals BA	Totals LA
o Communication	0%	6%
o Data Governance	7%	8%
o Data Governance: Data Quality	12%	12%
o Data Governance: Privacy & Security	7%	10%
o Organizational Culture	25%	22%
o Resources: Assets	14%	14%
o Resources: Humans	12%	9%
o Resources: Technical	16%	9%
o Weak pedagogical grounding	7%	10%

As table 6 shows, there are a lot of similarities in addressing challenges, with some slight variances between the two analytical domains. The differences slightly differ. The biggest difference is that BA addressed the sub challenge ‘technical’ more often compared to LA (16% versus 9%). Possibly because BA exists for a longer period of time and is considered to be more mature. Thus, more complex techniques can be used which implicates that BA is more experienced with the mismatch between business theories and pragmatic practices in comparison to LA. The maturity and business solutions confirm the recognized value of BA, where LA still struggles for showing value. Communication is more specifically named within LA, where BA mostly mentioned it in the context of organizational culture. It explains why organizational culture was mentioned slightly more at BA (25% versus 22%). LA names Data Governance, even though data governance wasn’t specifically named, slightly more than BA, which implies that there is a bigger need for expanding policies regarding Data Governance within LA. LA did not identify Data Quality in the literature. Yet Data Quality is addressed as much as within BA (12%). Something that is only named two times but could be interpret as an important one is the different focus of BA in regard to LA. BA focusses on turnover, production rates, numbers etc., while LA focusses on personal progression. Regulations such as GDPR can make it challenging for LA to be used at full potential because of working with anonymized data.

4.4 Solutions mentioned in interviews

The literature also indicated solutions. Additional solutions were identified during the interviews. The respondents described nine solutions. These are: (1) A fixed point of contact; (2) Clear goals that are in line with the vision strategy; (3) Clearly identify the needs; (4) Create independence: with training and empower workers for independent decision making; (5) Demonstrate value by showing results; (6) Getting the right people at the table; (7) Good documentation of governance; (8) Hiring (external) staff; and (9) User friendly, look & feel. Some of the mentioned solutions look similar to the solutions of the literature. Clearly identify the needs versus look at the specific needs of the teacher and learner, hiring (external) staff versus labor capacity, control of data, use of manuals and guidelines versus good documentation of agreements and last create independence: with training and empowering independent decision-making versus Empowering Key stakeholders.

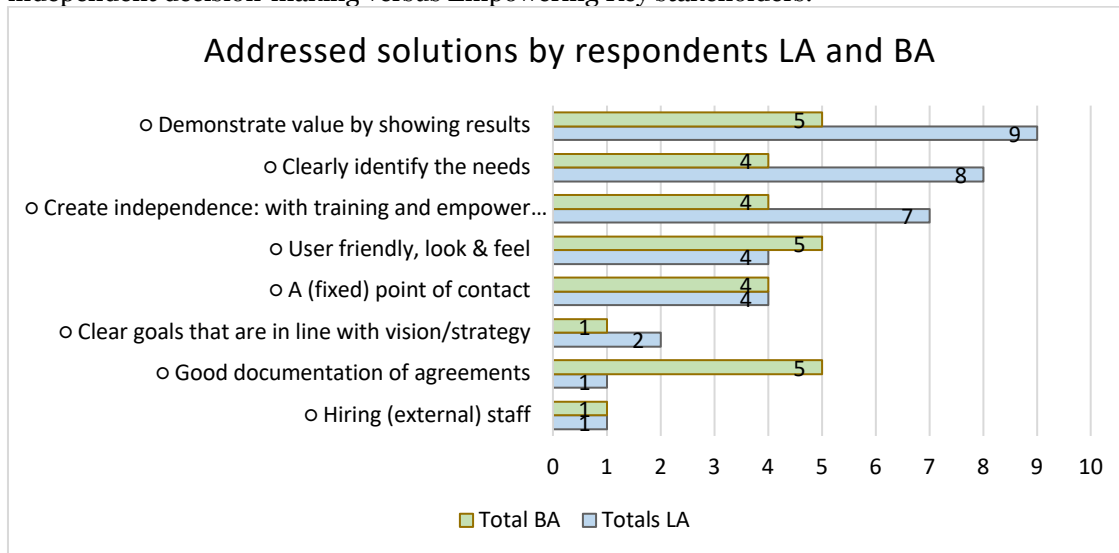


Figure 10: Addressed solutions by respondents LA and BA

“Showing results to create value” is the most frequent mentioned solution in both BA and LA. Three solutions are suggested within the new challenge communication. Clearly identify the needs, a (fixed) point of contact and good documentation of agreements. All of them are about clarity where and how to find the required information. Creating independence is focused on using training and promoting independent decision making. There needs to be time available before people are able to understand LA and to be able to make independent decisions about it. *‘It is not that much about the budget, it is more about the time. If I would do something, you have to do it with the people on the working floor, and they are incredibly busy (BLA2).’* and skilled people *‘The organization needs to build a pool up of skilled people (ULA3).’* To do so, goals need to be set within the line of the vision and strategy, so everyone looks in the same direction. The user friendly, look and feel was particularly focused on software packages with the ease of use and overall look and feel (think of colors, lay out etc.), paired with showing the correct data. Last solution, which isn’t named that much is to hire external staff. Which could be seen as contradictory. The most named challenge is the resources, a shortage of assets and people with the right skillset, yet the need for extra staff isn’t named that often as a solution. When putting the challenges and solutions together from both the literature and findings, table 8 connects the challenges to the corresponding solutions.

Table 8: Challenges, sub challenges and their solutions, combined from both literature and interviews. (in red new challenge from practice)

Challenge	Sub-challenge	Solution
Organizational Culture		<ul style="list-style-type: none"> - Empowering Key Stakeholders - Divide power structures
Weak pedagogical grounding		<ul style="list-style-type: none"> - Start on a small scale - Understanding and interpreting the data - Look at the needs of teacher and learner - Shared understanding of governance maturity - Continuous re-evaluation of data outcomes - Demonstrate value by showing results
Resources	Assets	<ul style="list-style-type: none"> - Create independence: with training and empower workers for independent decision making - *(1) Hiring (external) staff, to reduce workload
Resources	Humans	<ul style="list-style-type: none"> - Labor capacity - Hiring (external) staff to fill in vacancies
Resources	Technical	<ul style="list-style-type: none"> - IT investments - User friendly, look & feel of a system
Data Governance		<ul style="list-style-type: none"> - Control of data, use of manuals and guidelines - Clear goals that are in line with the vision / strategy - Good documentation of agreements
Data Governance	Data Quality	<ul style="list-style-type: none"> - *(1) Control of data, use of manuals and guidelines
Data Governance	Privacy & Security	<ul style="list-style-type: none"> - Ethics and legal requirements
Communication		<ul style="list-style-type: none"> - A fixed point of contact - Getting the right people at the table - Clearly identify the needs

*Note: Some of the solutions may appear more than one time when it is considered suitable within another challenge. They show a number in front if it appears twice (1) or more (2) (3) etc.

5. Discussions, conclusions and recommendations

5.1 Discussions

Within chapter five the research will be reviewed. The similarities and differences between the existing literature and research findings will be highlighted. The research will be reviewed according to the reliability and validity in terms of things that weren't done, actions that were not performed or other shortcomings. At the end, the research question and the corresponding sub questions will be answered. When reviewing the validity, the research was performed by only using interviews. There wasn't any documentation to prove the statements of the respondents. The documentation could have confirmed the statements, increasing validity. Second, during the collection of information, the questions developed over time due to the new insights. These ongoing adjustments in questions could have delivered different answers from earlier respondents. Third, in terms of generalizability the research only looks at four organizations within HEI and two out of the business domain. The research does provide enough interviews (12 in total) according to the literature, but the sample size could be considered to be minimal to generalize the findings.

5.1.1 What are challenges that withhold HEI from implementing Learning Analytics?

After collecting the information from both BA and LA respondents, the results showed that most of the challenges mentioned, show similarities with the literature (see table 7). It could be interpreted as a confirmation of the challenges in the literature are similar to the mentioned challenges within HEI.

Table 7: Challenges before and after interviews (in red new challenge from practice)

Identified challenges
Organizational Culture
Weak Pedagogical Grounding
Resources: Assets
Resources: Humans
Resources: Technical
Data Governance
Data Governance: Data Quality
Data Governance: Privacy & Security
Communication

The challenges were already identified, partly through LA literature and partly through BA literature. BA provided additions to the LA challenges. Most noticeable within LA, is that Data Quality wasn't specifically named in the literature. Within Tsai, Y. S. & Gasevic, D. (2017), Tsai, Y. S., Moreno-Marcos, P. M., Jivet, I., Scheffel, M., Tammets, K., Kollom, K. & Gašević, D. (2018b) the challenge was called ethics & privacy, where the focus was mainly on Governance policies. Yet, the results show a specific need for overall Data Governance policies within the Netherlands with emphasis on Data Quality. Figure 9 showed that Data Quality was mentioned within LA thirteen times, making it the most dominant sub challenge within Data Governance. A new challenge was identified from the interviews: the challenge communication. The challenge communication focusses on the lack of clarity where LA is used for and who to find for getting information about LA. The communication challenge could fit within other challenges such as Organizational Culture, but surely earns its right as an independent challenge. The challenges that withhold HEI for implementing LA are (1) organizational culture, (2) weak pedagogical grounding, (3) resources, (4) data governance and (5) communication.

5.1.2 What are challenges with similar implementation of Analytics at scale in Business Analytics?

Business Analytics is considered the more mature brother of Learning Analytics. Within Business Analytics present and past challenges could be of importance for LA. Sooner or later LA might become as mature as BA. With the knowledge that BA already encountered or even solved certain challenges, this could be of great value for LA. These additional information from BA provide insights and answers to (future) challenges of LA. The biggest difference between LA literature and BA literature was on the

focus of data governance: data quality. When looking at BA literature the challenge Data Governance showed a remarkable big focus on Data Quality (Fernandez, V., & Gallardo-Gallardo, E., 2020). BA uses the TOE-framework (Tornatzky and Fleisher, 1990) to examine organizations for the usability of BA. The Technological, Organizational and Environmental contexts are comparable with the identified challenges within LA literature. The interviews clearly showed that the literature was similar to the findings of the respondents. The challenges that are identified are: (1) Organizational culture, (2) weak pedagogical grounding, (3) resources and (4) data governance.

5.1.3 What are ways to overcome the identified challenges?

Various solutions are included within the literature. The findings offered additional solutions. These are: (1) A fixed point of contact; (2) Clear goals that are in line with the vision strategy; (3) Clearly identify the needs; (4) Create independence: with training and empower workers for independent decision making; (5) Demonstrate value by showing results; (6) Getting the right people at the table; (7) Good documentation of governance; (8) Hiring (external) staff; and (9) User friendly, look & feel. The most mentioned solution is to demonstrate value by showing results. All of these solutions belong to a corresponding challenge, as listed in table 8. The mentioned solutions from the interviews are highlighted in red.

5.2 Conclusions

This research intended to find the challenges within Dutch Higher Education to explain why LA is only used within local initiatives and not at scale. A lot of research about LA has been executed within other geographical areas, but not within the Netherlands. This knowledge gap within the Netherlands had to be examined. The previous chapters showed that there are a lot of different ways and challenges that can be identified within the field of scaling LA. As the problem statement stated: For what reasons do Dutch Higher Educational institutions (HEI) not systematically adopt Learning Analytics at scale?

We can conclude that within the Dutch HEI, there are multiple challenges that have to be faced before LA can be adopted at scale. The challenges overall are quite similar to the ones within other geographical areas, with one exception regarding the challenge communication. The conducted interviews confirmed what the existed literature had already indicated. Five challenges were mentioned during the interviews: (1) Organizational culture, (2) weak pedagogical grounding, (3) resources, (4) data governance and (5) communication. Challenges resources and data governance were mentioned the most, closely followed by organizational culture, weak pedagogical grounding and communication in that order. When looking more closely at resources: A shortage of people with the right skillset, lack of time and money and technical issues is the most common cause for not being able to scale LA within the Netherlands. LA literature partly identified data governance, but didn't identify data quality as a challenge. Yet it was mentioned the most within the challenge of data governance.

An important outcome of this research is the identification of a new challenge, "communication". Within communication there is the lack of clarity where LA is used for, no clear communication about LA-initiatives, unable to find the person (single point of contact) or department who are accountable within implementation and scaling of LA initiatives for retrieving information. This challenge is closely related to the challenge of Organizational Culture, yet the difference lies in clarity of communication and where to find information instead of behavioral, such as focus on acceptance of change. The literature also provided solutions to solve challenges. Figure 10 shows the specific order of the frequency of the named solutions, it implicates the importance to the respondents. The respondents named 'Demonstrate value by showing results' as the best solution.

5.3 Recommendations for practice

When encountering challenges for scaling LA within the Netherlands, it is likely to bump into the challenges regarding resources, data governance, organizational culture, weak pedagogical grounding and communication. When having to deal with the challenge of weak pedagogical grounding, where people don't know how to connect educational theory and pragmatic practice, try to deliver samples or demonstrations. These demonstrations visualize the possibilities of LA making people to understand and gain knowledge about the LA. Within resources make time available for people to train and get people familiar with LA, making their skillset more data-oriented. Furthermore, look at the possibilities of hiring extra staff to lower the pressure of work or try to find a way for good prioritization of work. When facing technical challenges, keep in mind that the user friendliness, look

and feel of a system is important to users. Try to include users with the selection and implementation of software.

For data governance there is a call for uniformity. Respondents addressed a need for a general document where data governance standards are offered, delivered by SURF or a similar institute. Within this document there needs to be clarity about the three different mentioned sub-challenges. First data governance in general: clear goals, flow of approval, documentation: providing manuals and guidelines, second data quality: availability, completeness and accessibility. Third data privacy and security: ethical dilemmas, privacy and security dilemmas regarding GDPR, confidentiality and compliance. In the end, communication is key, when facing the challenge communication look into finding clear communication lines, keep all the stakeholders in mind and try to involve them. Try to centralize communication through a single point of contact for LA initiatives to know where to find necessary information.

There is a whole range of methods to work efficient and effectively, such as Lean (DevOps, Kanban, Prince2, SAFe, Scrum etc.). Lean can be considered as a structured way to work in optimized working conditions and tackle most of the LA challenges. When looking into (a lack of) resources, lean focuses on prioritization according to the available resources (FTE available to do the work). The tendency of working in small batches with timeboxes of one to four weeks helps being adaptive to change. It reduces waste (in time). Within organizational culture lean is about being flexible and adaptive to change. The lean mindset is focused on demonstrating value, sharing and spreading knowledge about LA. Agile provides guidance and clarity to solve communication challenges: Starting from abstract goals that are split into smaller goals until it is split to tasks within departments. This enables departments in every level, from ground floor up to management to work within the goals of the company. It provides clarity, gets the right people at the table and people in all layers get accustomed to the new way of working.

5.4 Recommendations for further research

Within this research the challenges and their possible explanations within the Netherlands were identified. Providing enough employees with the data knowledge doesn't automatically mean there will be a change in culture. This research doesn't look into how to get to a data-informed culture. What aspects are of importance to get a data-informed culture? Furthermore, the literature showed that BA emphasized on data quality, while little was known about data quality in LA. This research confirmed that Data Quality is considered important to LA, yet not many articles address Data Quality within LA. What is the role of Data Quality for LA? In order to get more insights with more reliable and valid results, future research should include more respondents. Big samples lead to a higher reliability and validity.

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7. Appendix

Appendix 1: Challenges LA within the literature

List of the most common challenges according to the listed authors

- Literature that is being colored white, is the original table of Tsai et al. (2020).
- Literature that is highlighted green is added to the original table.
- Literature that is highlighted with orange is from outside the Learning Analytics field domain, but within other domains of Analytics.

Named challenges / author(s). Based on table of Tsai (2020)	Challenge 1: Organizational culture	Challenge 2: Weak pedagogical grounding	Challenge 3: Resources	Challenge 4: Ethics & privacy
Greller en Drachsler (2012)	x	x	x	x
Slade and Prinsloo (2013)	x			x
Elouazizi et al (2014)	x	x		
Monroy et al. (2014)		x	x	
Ferguson et al. (2014)	x	x		
Arnold et al (2014), Oster et al. (2016)	x		x	x
Macfadyen et al. (2014)	x		x	x
SURF (2015)		x	x	x
Arroway et al. (2016)			x	
Colvin et al. (2016)	x		x	x
Drachsler & Greller (2016)	x			x
Rodríguez-Triana et al. (2016)				x
Rubel & Jones (2016)	x			x
Ferguson et al. 2016)				x
West et al. (2016)	x			
Tsai & Gasevic (2017)	x		x	x
Dawson et al. (2018)	x		x	x
Tsai et al. (2018)	x		x	x
Gasevic et al. (2019)	x	x	x	x
Herodotou, Rienties, Boorwa et al. (2019)	x			
Pietro et al. (2019)	x			
Tsai et al. (2019)	x		x	x
Sanagustin et al. (2019)	x		x	x
Ferguson et al. (2019)				x
Knight, Gibson, Shibani et al. (2020)		x	x	
Kaliisa, Kluge & Mørch (2021)		x	x	x

Appendix 2: Challenges BA within the literature

List of the most common challenges according to the listed authors

Challenges	Stakeholder engagement and buy-in	Weak Pedagogical grounding	Resources	Ethics & privacy
Ramanathan et al., 2017;	x	x	x	
Vidgen, Richard and Shaw, S. and Grant, D.G., 2017;	x	x	x	x
M Attaran, S Attaran, 2018;		x	x	
Dursun Delen & Sudha Ram, 2018	x	x	x	x
Liu et al, 2018	x	x	x	
Moktadir et al., 2019;	x	x	x	x
Omar et al., 2019	x	x	x	
Ogbuke, Yusuf, Dharma & Mercango, 2020				x
Kumar, et al, 2020	x	x	x	
Fernandez, V., & Gallardo-Gallardo, E., 2020	x	x	x	x
Raut, Surendra Yadav, Cheikhrouhou, Narwane & Narkhede, 2021;	x	x	x	x

Appendix 3: Solutions to the challenges within the literature

Consisting of both LA and BA articles. Which are 25 articles in total addressing solutions to the challenges.

Authors	1.1	1.2	2.1	2.2	2.3	2.4	2.5	3.1	3.2	4.1	4.2
Grellen en Drachsler (2012)	x	x		x	x					x	x
Slade and Prinsloo (2013)		x								x	x
Elouazizi et al (2014)	x	x	x	x	x	x			x	x	x
Monroy et al. (2014)				x	x				x		
Ferguson et al. (2014)	x	x		x	x		x		x	x	x
Arroway et al. (2016)		x	x	x	x		x	x		x	x
Macfadyen et al. (2014)	x	x		x	x				x	x	x
SURF (2015)				x	x					x	x
Colvin et al. (2016)	x	x	x						x		x
Drachsler & Greller (2016)	x	x								x	x
Rodríguez-Triana et al. (2016)		x		x						x	x
Rubel & Jones (2016)										x	x
Ferguson et al. 2016)		x			x					x	x
West et al. (2016)	x	x		x	x		x	x	x	x	x
Tsai & Gasevic (2017)	x	x		x	x					x	x
Dawson et al. (2018)	x	x			x				x	x	x
Tsai et al. (2018)	x	x		x	x				x	x	x
M. Attaran, S. Attaran (2018)	x	x	x	x	x		x			x	x
Gasevic et al. (2019)	x	x	x	x	x			x		x	x

Herodotou, Rienties, Boorwa et al. (2019)	x	x	x	x	x	x				x	x	x
Pietro et al. (2019)	x	x	x	x	x		x			x	x	x
Tsai et al. (2019)	x	x			x	x				x	x	
Sanagustin et al. (2019)					x					x	x	x
Ferguson et al. (2019)	x	x	x	x	x						x	
Ogbuke, Yusuf, Dharma & Mercango (2020)											x	x
Knight, Gibson, Shibani et al. (2020)			x	x	x	x	x	x	x	x		
Kaliisa, Kluge & Mørch (2021)				x	x					x	x	x
Raut, Surendra Yadav, Cheikhrouhou, Narwane & Narkhede (2021)	x	x			x				x	x	x	x

Appendix 4: Interview questions regarding LA/ BA

NL (English on next page):

Beheerder

1. Zou je je kort willen voorstellen?
2. Wat versta je zelf onder LA/BA?
3. Ben jij tevreden hoe LA/ BA nu wordt gebruikt bij de organisatie?
 - a. Hoezo wel/ niet?
4. Met welk doeleind wordt LA/ BA ingezet?
5. Zie je nog kansen die benut kunnen worden binnen LA/ BA?
 - a. Weet jij waarom die (nog) niet zijn uitgerold?
6. Zijn er wel eens initiatieven gestart/ software gekocht waar bekend was dat collega's er niet op zaten te wachten?
 - a. Wat was de reden dat ze (of u) daar niet blij mee waren?
7. Wat is een mogelijke reden waarom een organisatie mogelijk geen gebruik zou maken van een nieuw systeem/initiatief?
8. Wat zijn redenen waarom organisaties wel gebruik maken van een LA/ BA-initiatief, is bekend welke waarde of functionaliteit het moet bevatten?
9. Bij het in gebruik nemen (implementeren) of opschalen (at scale) van nieuwe LA/ BA-software, waren er zaken die moeizaam gingen?
 - a. Wat ging er wel/niet moeizaam?
 - b. Hoe hebben jullie dit geprobeerd op te lossen?
10. Worden hierin duidelijke doelen gesteld? Worden die ook nageleefd?
11. Heb je hierin voldoende tijd en ruimte gehad zaken te regelen?
12. Heb je voldoende budget tot je beschikking?
13. Waren er aanspreekpunten waarmee kan worden geschakeld?
 - a. Kunnen deze aanspreekpunten ook echt wat teweegbrengen in de organisatie?
14. Voelen mensen zich verantwoordelijk om het systeem een succes te laten zijn?
 - a. Waar blijkt dat uit?
15. Werden er ook trainingen verzorgd om te leren werken met het systeem?
 - a. Was er ook genoeg tijd gereserveerd om bekend te raken met het systeem?
 - b. Is die kennis op orde binnen de organisatie?
16. Is het bij u bekend welke data wel en niet gedeeld mag worden met andere partijen, bijvoorbeeld met AVG of privacyvraagstukken?
 - a. Geldt dat ook voor de organisatie?
17. Is het ook wel eens mis gegaan? Dat een implementatie is mislukt?
 - a. Waar liep het op mis?
18. Zijn er andere zaken waar jullie tegenaan liepen die niet benoemd zijn?
 - a. Hoe hebben jullie dit geprobeerd op te lossen?

Gebruiker:

1. Zou je je kort willen voorstellen?
2. Wat versta je zelf onder LA/ BA?
3. Ben jij tevreden hoe LA/ BA nu wordt gebruikt bij de organisatie?
 - a. Hoezo wel/ niet?
4. Zie je nog kansen die benut kunnen worden binnen LA/ BA?
 - a. Weet jij waarom die (nog) niet zijn uitgerold?
5. Zijn er wel eens initiatieven gestart/ software gekocht waar je niet op zat te wachten?
 - a. Wat was de reden dat je daar niet blij mee was? Was dat een gevoel, of iets anders?
6. Wat is een mogelijke reden waarom je geen gebruik zou maken van een nieuw systeem/initiatief?
7. Wat zijn redenen waarom je wel gebruik zou maken van een LA/BA-systeem, welke waarde of functionaliteit moet het bevatten?
8. Bij het in gebruik nemen of opschalen van nieuwe LA/BA-software, waren er zaken die moeizaam gingen?
 - a. Wat ging er wel/niet moeizaam?
 - b. Hoe hebben jullie dit geprobeerd op te lossen?
9. Worden er duidelijke doelen gesteld, worden die nageleefd?
10. Voelde je je gehoord bij het ontwerp voor het gebruik van het nieuwe systeem.
 - a. Worden gebruikers meegenomen in het gebruik van het systeem? Waar bleek dat uit?
11. Heb je hierin voldoende tijd en ruimte gehad om mee te kunnen denken en zaken te regelen?
12. Had je de software snel onder de knie, was het makkelijk om te leren?
13. Zijn er meerdere mensen die keuzes kunnen en mogen maken aangaande de LA/BA-software?
 - a. Zijn er autorisatie structuren?
14. Voelen mensen zich verantwoordelijk om het systeem een succes te laten zijn?
 - a. Waar blijkt dat uit?
15. Werden er trainingen aangeboden om te leren werken met het systeem?
 - a. Was er ook genoeg tijd gereserveerd om bekend te raken met het systeem?

16. Is bij jou bekend welke data wel en niet gedeeld mag worden met andere partijen, bijvoorbeeld met AVG of privacyvraagstukken?
 - a. Geldt dat ook voor je collega's?
17. Zijn er andere zaken waar jullie tegenaan liepen die niet benoemd zijn?
 - a. Hoe hebben jullie dit geprobeerd op te lossen?

EN:**Administrator (or similar)**

- Would you like to introduce yourself?
- How would you define LA. BA?
- Are you satisfied how LA/ BA is currently used within your organization? Why yes/no?
- With what purpose is LA being used?
- Do you see any chances that can be used within LA/BA? Can you explain why these aren't implemented yet?
- Were there initiatives that were started or bought where colleagues weren't happy about? Do you know why?
- What is supposedly a reason to not use a new system or initiative? W
- What are reasons why organization use of a LA/Ba system, is it known what value or functionality it must possess?
- When using or scaling new LA/BA-software, were there things that didn't went smooth?
 - o What did go smooth and what didn't?
 - o How did you try to fix this?
- Are clear goals being communicated? Do people work along the goals?
- Do you have sufficient budget available?
- Are there point(s) of contact for communication? Do these point(s) of contact have some sort of authority?
- Do people feel responsible to make initiatives a success? Can you explain why?
- Are training being offered to learn to work with LA initiatives?
- Did you have plenty of time available to get accustomed to work differently?
- What do you know about GDPR / privacy regarding LA?
- Did it happen that an implementation failed? Why did it go wrong?
- Are there other things that weren't named? How did you try to fix this?

User (or similar)

- Would you like to introduce yourself?
- How would you define LA. BA?
- Are you satisfied how LA/ BA is currently used within your organization? Why yes/no?
- With what purpose is LA being used?
- Do you see any chances that can be used within LA/BA? Can you explain why these aren't implemented yet?
- Were there initiatives that were started or bought where colleagues weren't happy about? Do you know why?
- What is supposedly a reason to not use a new system or initiative? W
- What are reasons why organization use of a LA/Ba system, is it known what value or functionality it must possess?
- When using or scaling new LA/BA-software, were there things that didn't went smooth?
 - o What did go smooth and what didn't?
 - o How did you try to fix this?
- Are clear goals being communicated? Do people work along the goals?
- Do you have sufficient budget available?
- Are there point(s) of contact for communication? Do these point(s) of contact have some sort of authority?
- Do people feel responsible to make initiatives a success? Can you explain why?
- Is training being offered to learn to work with LA initiatives?
 - o Did you have plenty of time available to get accustomed to work differently?
- What do you know about GDPR / privacy regarding LA?
- Did it happen that an implementation failed? Why did it go wrong?
- Are there other things that weren't named? How did you try to fix this?
- Did you feel involved when implementing new initiatives?
- Were users involved, how so?
- Did you have plenty of time to dig in, think accordingly and arrange things?
- Was it easy to learn the initiatives?

Lay-out Interview, retrieved from the SHEILA Framework (2018).