# MASTER'S THESIS

## Learning Analytics Capability Model

## A journey from a learning analytics input model toward a more substantiated process model.

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**Award date:**
2023

# Learning Analytics Capability Model:

## A journey from a learning analytics input model toward a more substantiated process model.

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| Opleiding: | Open Universiteit, faculteit Betawetenschappen<br>Masteropleiding Business Process Management & IT |
| Degree programme: | Open University of the Netherlands, Faculty Science<br>Master of Science Business Process Management & IT |
| Course: | IM0602 BPMIT Graduation Assignment Preparation<br>IM9806 Business Process Management and IT Graduation Assignment |
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| Date: | 17/02/2023 |
| Thesis supervisor | Justian Knobbout |
| Second reader | Ben Roelens |
| Status: | final version |

# Abstract

This research aims to contribute to a better understanding of the Learning Analytics adoption process. This is to make educational institutions more willing to use Learning Analytics. To allocate resources to reach a certain maturity level, it would be beneficial to know in what order to develop capabilities. This thesis provides an answer to the main research question: *In what order and at what level should educational institutions develop learning analytics capabilities to successfully deploy Learning Analytics?*

To answer the research question an extensive literature review was conducted. From this, a theoretical framework was outlined based on some models, which were further elaborated and finally applied within focus group discussions at three Dutch higher education institutions. The outcomes of this discussions are a Learning Analytics capability process model. This model was established based on the consensus between the three educational institutions and aims to test the theoretical perspective of experts against what is experienced or done in practice. The process model divides the development of the capabilities into several phases and thus forms an answer to the proposed research question. The insights obtained can form a basis for arriving at a refined Learning Analytics capability process model.



# Key terms

Learning Analytics, Capability model, Process model, Adoption of Learning Analytics, Maturity of Learning Analytics

## Summary

Learning Analytics (LA) is part of the broader global evolution of digitization, big data, increasing use of the Internet, and the increasing power of algorithms and in particular artificial intelligence. This evolution will also materialize more and more in the educational context. The process of collecting, analysing, and using student data to perform interventions to improve education is called learning analytics. Over the years, several models have been developed to overcome implementation challenges and support the adaptation of LA. Three kinds of models can be found in the literature: input, output, and process models. input models outline the requirements for what is needed for LA adoption. Output models focus on the dimensions and what outcomes to expect from LA. Finally, process models are looking to implementation as an iterative and continuous process. Process models are better able to capture the complexity of higher educational institutions rather than input models.

A new capability model has been designed recently. The new model should remedy the shortcomings of the previous models and the model pays attention to what resource-based capabilities are necessary for the adoption of LA and how to operationalize these capabilities. More research is needed on the process behind the adoption of LA at higher educational institutions (HEI). During the implementation process, it is likely that there will be some capabilities that need development at the start of the process, while other capabilities are more necessary at the end of it. To allocate resources to reach a certain maturity level, it would be beneficial to know in what order to develop capabilities. This thesis provides an answer to the main research question: *In what order and at what level should educational institutions develop learning analytics capabilities to successfully deploy LA?*

Maturity models are a tool for capability development and foster the development of capabilities along a path of predefined stages. The maturity model for LA used in this thesis consists of four stages: ‘ad hoc’, ‘initial’, ‘structural’, and ‘systematic’. A maturity model says nothing about the order in which the different capabilities should be developed. To handle this an implementation timeline has been used in this thesis. This implementation timeline can be used as additional guidance for LA implementations at scale. The timeline consists of four phases: first, an initialization phase, followed by a prototyping phase, a piloting phase, and finally a scaling phase. Within this research, the previously mentioned capability model will be refined. This model can be classified as an input model. The goal is to turn this into a process model to find out if capabilities for LA should be developed at different stages of the previously mentioned implementation timeline.

The research was conducted at three educational institutions in the Netherlands through focus group discussions held with employees involved in the use of LA. The researchers have coded the qualitative data to identify themes or patterns for further analysis, related to the central research question. Co-occurrence and co-document analyzing techniques were used to explore relations and interesting findings in the data.

During the focus groups, the educational institutions’ maturity level with regard to learning analytics was determined. Both the first and the second educational institutions seem to belong to the 'structural' level. It can be concluded that the third educational institution is between the 'structural' and the 'systematic' level. The outcome of this research is a process model for Learning Analytics. This model shows more depth because it adds a time dimension compared to the existing models. The model is a representation of how the three participating institutions perceive capability development on the implementation timeline. Further, the LA capability process model tests the theoretical perspective of experts against what is experienced or done in practice. There is consensus for certain capabilities between the conceptual model and the findings conducted at the three HEI. For other

capabilities, no agreement can be established between the conceptual model and the outcomes of the three focus group discussions. In addition, a remarkable conclusion is that for 11 capabilities a consensus has been found between the three educational institutions, all starting from the initialization phase.

This thesis provides several recommendations HEI needs to make sure that LA implementations are well prepared. Consider and consult with the stakeholders involved when certain capabilities need to be developed. Allocate the necessary skills and knowledge, when appointing the team. Strive for quality and have a strategy to follow. Base your work on policies and best practices. Start with the elaboration of your Privacy & Ethics regulation and ensure the necessary infrastructure and system properties. Continuously monitor the implementation performance and finally ensure that your stakeholders remain involved. These recommendations are based on the findings of the first and third research questions, namely the order in which LA capabilities should be developed and what capabilities are required for the successful adoption of LA.

# Acknowledgment

This master's thesis is the final piece of the master's program in Business Process Management & IT. Writing this thesis has been a very instructive and fascinating challenge. I would like to thank all the people who directly or indirectly contributed to the realization of my master's thesis. First of all, I would like to thank the study group of which this research topic is a part. I would like to thank my promotor, Justian Knobbout, for providing guidance and advice to help me complete this thesis. I would also like to thank my co-researcher, Linda Lieferinck, for the positive collaboration.

Finally, I would like to pay tribute to my family, who have always supported me unconditionally, even in the most difficult times. I think of my mother, brothers, and sisters-in-law. In particular, I would like to honor my father, Marc Schelkens (†), who passed away while I was studying at the Open University. He has always been an inspiration to me, a listening ear, and without him, I would never have been where I am today.

# Contents

# 1. Introduction

## 1.1. Background

The widespread use of the Internet, computers, mobile devices, and software systems such as learning management systems (LMS)[1] is driving a data explosion in educational settings (Lang & Siemens, 2011). While attending a class, reading a book, or having a discussion in the hallway used to be elusive, explicit data is now available and produced and maintained in learning environments. Students, lecturers, and study career counselors leave behind digital traces through the use of educational systems. Higher education institutions (HEI) have been using information systems for years, which store data at varying levels of granularity. These institutions are increasingly reaching a higher level of maturity in the use of the data they have stored. However, they have not yet succeeded in using the data on a large scale to improve education (Romero & Ventura, 2020). The process of collecting, analysing, and using these student data to implement interventions to improve education is called learning analytics[2] (LA) (Clow, 2012)

Over the years, several models have been developed to overcome implementation challenges and support the adoption of LA. Three kinds of models can be found in the literature, those are input, output, and process models (Broos et al., 2020). Within the current research, those adoption models and a capability model (2020) designed by Knobbout and his colleagues will be further studied. The latter model pays attention to what resource-based capabilities are necessary for LA adoption and how these capabilities can be operationalized (Knobbout et al., 2020). This capability model can be classified as an input model. Transforming this input model into a process model would be beneficial, as process models are better able to capture the complexity of HEI rather than input models (Broos et al., 2020). A good process model contains both sequence and depth and this brings us directly to the reason for this research. The objective of this research is to gain a better understanding of the already designed capability model and how it could be enhanced to facilitate the adoption of learning analytics at higher educational institutions. Facilitating adoption could lead to a higher level of maturity in LA, which in turn could lead to better student self-guidance, improved student learning achievement, improved educational excellence, improved student satisfaction, and improved student retention.

## 1.2. Exploration of the topic

Learning Analytics in higher education is part of the broader global evolution of digitization, big data, increasing use of the Internet, and the increasing power of algorithms and in particular artificial intelligence[3]. This evolution will also increasingly manifest itself in the educational context (De Laet et al., 2018). Developments such as online education and blended learning[4] are bringing about major changes. One of them is that teachers have less insight into what students are doing. In a classroom, teachers notice the degree of engagement with course materials and interaction with the students. It is clear whether they are there or not, whether they are participating, and whether they have completed their assignments. This overview is lacking in an online education environment. The use of data in education could provide a solution to this (Joksimovic et al., 2019). The applicability of LA can

[1] An LMS is a software that supports the creation, management, organization, and delivery of online course material to a target group.
[2] Learning Analytics is the measurement, collection, analysis, and reporting of data about learners and their contexts, for purposes of understanding and optimising learning and the environments in which it occurs.
[3] The ability of a machine to exhibit human-like abilities - such as reasoning, learning, planning, and creativity.
[4] combination between digital and analog education.

be classified into the following three domains: research into learning processes in education; optimization and personalization of the learning environment and, finally, study career counseling (De Laet et al., 2018).

A concrete example of an LA application can be found at KU Leuven. This educational institution decided in 2015 to investigate how existing data can be used to provide feedback to students during the transition from secondary school to higher education. As a result of this initiative, first-year students now receive a dashboard four times a year that provides insight into their learning-, study skills, and academic results. Furthermore, the dashboards also provide insights to the students to make possible improvements. As a result of this initiative, the institution is experiencing that students contact the study career counselor more often and earlier in the semester. (van Trigt, 2019).

Avella and colleagues (2016) conducted a systemic literature review on the methods, benefits, and challenges involved in applying LA in higher education (Avella et Al., 2016). Their research revealed that LA uses various methods including visual data analysis techniques, social network analysis[5], semantic[6], and educational data mining[7] including prediction[8], clustering[9], relationship mining[10], discovery with models, and separation of data for human judgment to analyse data (Avella et Al., 2016). They identified seven benefits that can come from applying LA. These are targeted course offerings; curriculum improvement; student learning outcomes, behaviour, and process; personalized learning; improved instructor performance; post-educational employment; and improved research in education (Avella et Al., 2016). Finally, implementing LA in a higher educational environment poses certain challenges. Challenges include issues related to record keeping, data collection, process evaluation, data analysis; lack of connection with learning sciences; optimizing learning environments, emerging technology, and ethical & privacy issues (Avella et Al., 2016).

## 1.3. Problem statement

Over the years several models have been developed to overcome implementation challenges and support LA adoption. Three types of models can be found in the literature, namely input, output, and process models (Broos et al., 2020). Input models focus on the dimensions required for LA adoption. An Output model focuses on the dimensions and the expected results. Finally, the process models assume a series of processes to achieve LA adoption. An overview of the strengths and weaknesses of the different model types can be found in the below table.

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[5] Social network analysis (SNA) is a collection of methods and tools that could be used to study relationships, interactions, and communications.

[6] Semantic Data Mining refers to the data mining tasks that systematically incorporate domain knowledge, especially formal semantics, into the process.

[7] Educational Data Mining is an emerging discipline, concerned with developing methods for exploring the unique and increasingly large-scale data that come from educational settings and using those methods to better understand students, and the settings in which they learn in.

[8] Predictive analytics is a branch of advanced analytics that makes predictions about future outcomes using historical data combined with statistical modelling, data mining techniques, and machine learning.

[9] Clustering is the task of dividing the population or data points into several groups such that data points in the same groups are more similar to other data points in the same group and dissimilar to the data points in other groups.

[10] Relationship mining is the task of identifying the different relations that might exist between two or more named entities.

| Model type | Strengths | Weaknesses |
|---|---|---|
| Input | - A quick insight into what dimensions are important<br>- Consider a variety of dimensions, not only data/technology | - Unclear how to be operationalized<br>- Little attention to interaction between dimensions<br>- Often abstract and generic |
| Output | - Considers the desired outcomes<br>- Map development over time | - Barely addresses the complexity of implementation<br>- Do not deliver specific guidelines |
| Process | - View implementation as an iterative and continuous process<br>- Capable of dealing with the complexity of implementation | - Empirical validation is yet low<br>- No practical guidelines on how to be operationalized |

*Table 1: Comparison of existing models (Knobbout, 2021)*

Recently a new capability model has been designed by Knobbout and his colleagues (2020). They have tried to remedy the shortcomings of the above-mentioned models and the design is based on insights they received from Dutch higher education institutions (HEI) (Knobbout et al, 2020). A graphical representation of the model can be found below.

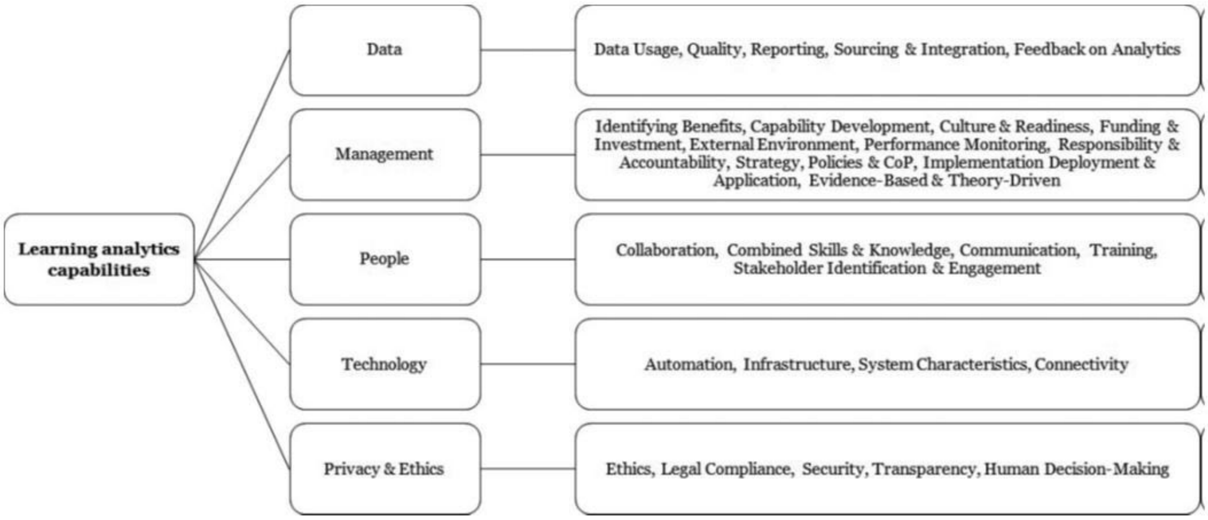


*Figure 1: Capability Model for LA (Knobbout et al., 2020)*

In the literature, a capability is defined as the ability to achieve a certain goal using available resources (Bharadwaj, 2000). This model pays attention to what resource-based capabilities are necessary for the adoption of LA, how to operationalize these capabilities, and which capabilities must be developed at which stage of the implementation process (Knobbout, 2021). As already mentioned above, models can be divided into three types of models: input, output, or process models. This capability model can be classified as an input model. Transforming this input model into a process model would be beneficial as process models are better able to capture the complexity of HEI rather than input models (Broos et al., 2020).

This research aims to contribute to a better understanding of the adoption process. This to make educational institutions more willing to use LA. If LA were applied more and more, education would benefit and higher quality could be achieved. Which would ultimately be beneficial for the students. But to achieve this, educational institutions must learn to implement LA. At present, this is often still too limited or insufficient. This research aims to contribute to solving this problem. More research is needed on the process behind LA adoption at HEI. During the implementation process, it is likely that some capabilities will need to be developed at the beginning of the process, while other capabilities will be more needed at the end of it. For allocating resources to reach a certain maturity level of a capability, it would be helpful to know which capability needs to be developed and in what order (Knobbout, 2021).

## 1.4. Research objective and questions

The main objective of this research is to gain a better understanding of which capabilities are needed at what time when implementing LA in an HEI. The focus will be rather on the recently developed capability model as this is an all-encompassing model targeting Dutch higher educational institutions. More research is needed on how to implement LA capabilities. The maturity of institutions concerning LA adoption and the processes behind will be studied in more detail. Articles like the one by Freitas et al., (2020) about maturity models and the one by Broos et al., (2020) about the implementation timeline are giving some insights into this matter. The main aim of the research is to enhance the capability model so that it becomes more suitable to use when an HEI wants to adopt LA.

The above can lead us to the following main research question:

*In what order and at what level should educational institutions develop learning analytics capabilities to successfully deploy LA?*

This main research question is divided into smaller sub-research questions. So that an answer to the sub-questions can formulate an answer to the main research question. The following sub-questions are formulated:

- *In what order should LA capabilities be developed?*
- *What are the different maturity levels LA capabilities can have?*
- *What capabilities are required for the successful adoption of LA?*

When an answer to the above questions can be found, it will provide a better understanding of how Dutch HEI adopted LA. This knowledge and insights should be used to improve the capability model, which is the main objective of this research.

## 1.5. Motivation/relevance

This research aims to provide a better understanding of the process behind the adoption of LA in HEI. For students, this research may be indirectly beneficial as their educational institutions manage to achieve higher LA maturity levels. Students are often involved in the benefits of learning analytics. For example, their learning environment can be more optimized and personalized, a higher student and teacher performance, a more tailor-made study career guidance, etc. Further, this report may be of added value to LA practitioners, researchers & senior Management of HEI, who want to learn more about how to further develop LA capacity within their institution. A better understanding of the adoption process and knowing which capability to develop first may lead to a more efficient and effective way of implementing LA at educational institutions. It might be that step of reaching a higher level of maturity or being more confident about taking the next step in the adoption process.

## 1.6. Main lines of approach

This master thesis consists of an introduction, a theoretical framework, a methodology, results, and a discussion part, conclusions, and recommendations. In the introduction, attention is paid to the central problem statement and the central research question is defined. Secondly, the theoretical framework will further explore the problem statement by searching for relevant literature on the topic. In methodology, the main purpose is to explain what decisions have been made regarding the research method. The fourth chapter presents the data of the performed analysis as defined in the research approach from the methodology chapter. The main purpose of this chapter is to present the data collection of the study. In the final chapter, the findings of the research conducted can be found and how they relate to the existing knowledge within the researched field. Here, there will be room to discuss, reflect and conclude those findings, and further recommendations will be made.

# 2. Theoretical framework

In this section, the method and approach of the literature review are described. The approach is elaborated in the first paragraph. This is followed in the second paragraph by a review of the implementation, followed by the answers to the first three sub-questions and the refinement of the research objective.

## 2.1. Research approach

An extensive literature review has been conducted inspired by the approach as it is described by Brendel and his colleagues. (Brendel et Al., 2020) This method makes use of six steps: preparation, Define scope, literature search, analysis, synthesis ,and discussion. Three data sources are used the Open University digital library, google scholar ,and the database of the institute of educational sciences. The aim of working with these three different search engines was to avoid missing any relevant articles. Further, The literature research has been conducted by making use of some inclusion criteria to improve the quality of the literature, the readability ,and the limitation of the result. A complete elaboration of the research approach can be found in appendix 7.1.

## 2.2. Implementation

In carrying out this literature search, a self-designed Excel template was used to keep track of and document all literature found. In addition, the various subqueries with associated parameters were also documented. In this way, the number of articles found and the final number of articles selected were noted for each partial query. The literature research resulted in 1160 articles found. A first selection has been applied to the relevance the abstract of the article shows with the predefined research question. After this first selection criteria, 34 relevant articles remained. The second selection criterion was proofreading the full article. This resulted in a final selection of 22 relevant articles. By reading the full articles, eight articles could be identified as core articles, meaning that those eight articles contain a lot of useful information to describe and answer the predefined research questions. Please note that a complete description of the research execution can be found in appendix 7.2. The results of this literature research can be consulted in appendix 7.3.

## 2.3. Results and conclusions

Within this theoretical framework, an extensive literature review has been conducted. The review is systematic as a predefined and systematic methodology has been used. In this chapter, more information will be provided, so it can function as a bridge between the previous chapter and the following one, where the methodology of the research will be further described.

### 2.3.1. Learning analytics adoption

First, will be started with the concept of LA adoption. The literature states that to establish LA sustainably, HEI must align its adoption of it with its institutional vision and goals (Siemens et al., 2013). Moreover, HEI need a strategic planning process to overcome institutional resistance to innovation and change (Macfayden et al. 2014). The SHEILA project (Supporting Higher Education to Integrate Learning Analytics) was launched in 2016 to assist HEI to become mature users and conservators of the digital data of their students. A framework has been developed to assist with policy and strategy formation processes for the institutional adoption of LA (Tsai et al., 2018).

The SHEILA framework was built using the RAPID Outcome Mapping Approach (Macfayden et al. 2014). This model consists of seven steps and is even slightly adapted to the LA context: 1.) Define a clear set of overarching policy objectives 2.) Map the context 3.) Identify the stakeholders 4.) Identify learning analytics purposes 5.) Develop a strategy 6.) Analyse capacity; develop human resources 7.) Develop a monitoring and learning system (evaluation). This framework for LA adoption guides users from the initial policy objective to the final evaluation (Ferguson et al., 2015).

Even though these frameworks have already proven their worth, they often only focus on specific elements such as policy or privacy and ethics or lack descriptions on how to operationalize important dimensions. Those shortcomings limit the practicality of the frameworks and only help HEI to a certain degree (Knobbout et al., 2020). In addition to the frameworks just described, the literature consists of several frameworks that have been developed. In summary, Colvin and colleagues identified nine different frameworks to support LA implementation and from these, five dimensions can be considered that have an impact on implementations: technology readiness, leadership, organizational culture, workforce and institutional capacity, and LA strategy (Colvin et al., 2016).

For systemic institutional adoption and implementation of LA, usable and understandable adoption models must be used. Without models specifying how existing processes and practices can be adopted to support learning analytics, institutions are facing the risk of generating problems that either postpone or disable the implementation of LA (Gasevic et al., 2019).

Addressing key institutional priorities is essential for successful LA adoption. The transformation that the adoption entails must take into account some critical dimensions (Gasevic et al., 2019):

1. Building the institutional policy and strategy for learning analytics.
2. Establishing effective leadership models to drive and oversee implementation.
3. Defining principles for privacy protection and ethical use of analytics.
4. Implementation of learning analytics tools catering the primary stakeholders.
5. Development of analytics-informed decision-making culture.

In the literature two adoption processes are identified, Solutions oriented (analytics implemented to address a specific issue) or process-oriented (analytics implementation fostered through experimentation and innovation) (Colvin et al., 2016). Colvin et al. (2016) noted that all HEI could be situated into one of the two adoption processes. The focus of institutions following a solution-oriented approach is mainly on the use of LA to resolve concerns with student retention. While the second group of institutions applies LA to help promote the understanding of learning and teaching. The former focused on acquiring technical solutions, while the latter focused more on institutional complexities and multi-stakeholder involvement (Colvin et al., 2016).

These findings are in line with the research conducted by Tsai and colleagues, they have researched the change of priorities when institutions experience with LA increases. Institutions that have less than one year of experience in adopting LA are adopting LA as a measuring tool for institutional performance. Those institutions showed a problem-solving approach targeting student retention as their main goal. In contrast, HEI with more than one year of experience is showing a growing interest in understanding a teaching or learning phenomenon to enhance teaching. They follow an exploratory approach to get a better understanding of the learning phenomenon (Tsai et. al., 2021).

As institutions gain experience with LA, their conceptualization of LA changes, and the perception of LA as a solution model shifts to an innovation model (Tsai et al., 2021). In line with this observation, Viberg and her colleagues identified a trend of movement from measuring and predicting drop-outs to exploring student learning experience as the field of LA matures (Viberg et al.,.2018). When institutions experience with LA adoption matures a movement from a measuring culture to an exploratory one happens, a movement from a data-centred concern to a methodology-centred concern, and an involvement of high-level stakeholders to a more equal engagement with primary-level stakeholders (Tsai et al., 2021).

Critical success factors (CSFs) refer to these factors that are critical to the success of any organisation (Clark et al., 2020). Clark and her colleagues took the concept and applied it to the implementation of LA in HEI. In the context of LA system implementation, the modified framework consists of five dimensions: strategy and policy at the organisational level, Information technical readiness, performance and impact evaluation, people's skills and expertise ,and data quality (Clark et al., 2020). Out of the five dimensions, people's skills and expertise ,and data quality are perceived as key aspects of LA implementation (Clark et al., 2020). Data quality is crucial to guarantee success. All data sources needs to be reliable and the integrity of the data need to be maintained to guarantee that users have confidence in the information that the LA system offers (Clark et al., 2020). The emphasis on people underlines the essential role of human intervention in technology adoption. This dimension focuses on the need for a competent team with the right skills and the competencies of the project manager (Clark et al., 2020). The strategy and policy dimension stress the need for managerial support both financially and strategically. Last, The HEI should show technological readiness, this means that there needs to be a considerable infrastructural upgrade allowing institutional-wide adoption and promoting scalability (Clark et al., 2020). Those five dimensions are giving an idea of what capabilities are needed for the successful adoption of LA, so what has been described above should bring a better understanding of the third sub-research question.

### 2.3.2. Learning analytics capabilities

Capability development is closely related to the resource-based view of the firm and dynamic capability theory. The resource-based view argues that organizations are collections of resources that achieve competitive advantage if their resource configuration is valuable, rare, imperfectly imitable, and non-substitutable (Barney, 2000; Penrose, 1959; Wernerfelt, 1984). Resources can be split into assets and capabilities. Assets are anything tangible or intangible that can be used by an organization, capabilities refer to the ability to perform a coordinated set of tasks for achieving a particular result (Helfat & Peteraf, 2003) The Dynamic capability theory is an extension of the resource-based view in that it distinguishes between operational and dynamic capabilities (Pavlou & El Sawy, 2011). Operational capabilities refer to the basic functioning of an organization and its ability to make a daily living. Dynamic capabilities help, integrate, build ,and reconfigure operational capabilities to increase their fit with the organization's environment and to improve effectiveness (Zollo & Winter, 2002).

#### 2.3.2.1. Maturity model for the learning analytics domain

Maturity models are a tool for capability development that has become increasingly popular over the last decades (Harmon, 2009; Pöppelbuß et al., 2011). Maturity models foster the development of capabilities along a path of predefined stages (Mettler, 2011). These stages express to what extent a certain capability has been developed, but say nothing about the order in which the different capabilities should be developed. Maturity models distinguish two layers of capability development, namely the capability area layer and the organizational layer (de Bruin et al., 2005). The capability area layer focuses on capability areas. Each capability area has a capability level that expresses the extent to which that capability is developed. The organizational layer focuses on maturity, the interplay ,and aggregated effect of all capability areas (van Looy et al., 2011).

What has been described above has been derivated from non-LA literature. although, LA literature also describes the use of maturity models. In what follows a description will be given of a maturity model used for Learning analytics. In the study conducted by Freitas and colleagues, a Learning analytics Maturity Model (MM) has been developed. The authors argue that a maturity model consists of a sequence of maturity levels that represent an anticipated, desired ,or typical evolution path for an educational institution shaped as discrete stages. A maturity model can be seen as a roadmap for a given area that identifies the key activities to support an HEI to reach higher levels of maturity in its processes (Freitas et al., 2020). Each maturity level improves an HEI progress toward excellence. Therefore, the level definition makes it possible to understand the current situation of an institution in the context of LA and the benefits to be gained from advancing to a higher maturity level (Freitas et al., 2020).

| Maturity Level | Description |
|---|---|
| 4: Systematic | - LA becomes institutionalized<br>- Funding for existing and new projects<br>- Solutions are increasingly effective in meeting the priorities of the HEI & other stakeholders<br>- LA leader has the autonomy to decision making |
| 3: Structural | - Senior management involvement<br>- Goals are defined to be achieved by using LA<br>- Increase in complexity of developed tools<br>- More robust infrastructure<br>- Formally established leadership |
| 2: Initial | - LA has also been adopted in other departments<br>- Greater stakeholder involvement<br>- Tools are evaluated & enhanced by user feedback<br>- More extensive coverage of LA projects<br>- Greater engagement & Understanding of the role of LA<br>- Regulations defined by the institution regarding students privacy<br>- Initial initiatives for training on LA tools |
| 1: Ad Hoc | - Beginning of LA adoption<br>- Initiatives of individual stakeholders<br>- No formal established processes<br>- No planning of LA objectives<br>- Only with available tools |

*Table 2: Overview of Maturity levels*

Here too, an HEI can only reach a different, higher maturity level if the criteria of the previous maturity level have been reached. In this way, an institution can incrementally grow to a more mature level of LA adoption. What has been described above gives a better understanding of the different maturity levels LA capabilities can have, which can be seen as an answer to the second sub-research question. The different maturity levels can also be seen as the degree of success at which the HEI adopts LA. An HEI that can reach the highest maturity level is successful in adopting LA at its institution.

### 2.3.3. Order of capability development

To answer the first research question, the study by Adejo & Connolly (2017) was examined in more detail. This study provides a roadmap that can be used in the implementation of LA at the institutional level. The roadmap consists of five phases: the preliminary planning phase; the security, privacy, and compliance phase; the roadmap development phase; the adoption and evaluation phase, and the monitoring and control phase (Adejo & Connolly, 2017). In the study of Broos et al., (2020) a similar implementation timeline has been used to orchestrate the interaction between policy-making and implementation. This implementation timeline can be used as additional guidance for LA implementations at scale. The timeline consists of four phases: first, an initialisation phase, followed by a prototyping phase, a piloting phase, and finally a scaling phase (Broos et al., 2020).

*Initialisation phase:*

In the first phase, it is important to create a common understanding of which problems will be targeted and the basic needs for the LA project. A project team needs to be assembled and summary-level planning should be defined (Broos et al., 2020).

*Prototyping phase:*

Typical activities may include prototyping and several iterations of consulting stakeholders to better elicit requirements and validate the design choices and assumptions addressed by the prototypes. The prototypes are used as an instrument to support the design activities, discussion, and improvement through iteration (Broos et al., 2020).

*Piloting Phase*:

This phase aims at testing the solution design in a natural setting. It involves the use of real data and real users in a context that is representative of the intended goal of the solution. Only a subset of the intended user population is targeted. Piloting can also be organized as a sequence of iterations (Broos et al., 2020).

*Scaling phase:*

The last phase starts from what was learned from the previous phases to re-implement or at least re-deploy the envisioned solution at scale. Here the full population is targeted: all intended courses, programmes, and faculties (Broos et al., 2020).

The discussed Roadmap or the implementation timeline are both instruments that bring additional guidance for LA implementations. In that way that implementation tasks can be assigned to a certain phase and executed in a certain order. Those insights provided here give a partial answer to the first sub-research question. It remains unclear which exact capabilities are needed to be developed in which phase. To provide a more complete answer practical research will be conducted with the use of focus group discussions.

## 2.4. Objective of the follow-up research

The main aim of this research is to gain a better insight into which capabilities are needed at what time when implementing LA at an HEI. This research aims to provide a better understanding of the process behind LA adoption at the institutional level. Within this research, the previously mentioned capability model developed by Knobbout (reference figure 1) will be further elaborated by evaluating its design. This capability model can be classified as an input model. The goal is to turn this into a process model to find out whether capabilities for LA should be developed at different stages of the adoption. Those different phases could be identified as found during the literature search. Referring to the implementation timeline used by Broos et al., (2020). A good process model contains both sequence and depth and this brings us directly to the reason for this research. The aim is to determine whether higher education institutions develop their LA capabilities in different phases or by using a certain timeline as described in the literature. Then to find out which capabilities they develop first and which ones later. A better understanding of the adoption process and knowing which capabilities to develop first could potentially lead to a more efficient and effective way to implement LA in educational institutions.

# 3. Methodology

In this section, the method and design of the research are described. The research method is elaborated in the first paragraph. This is followed in the second paragraph by the technical design of that method, followed by an explanation of the data analysis technique and a reflection on dependability, credibility & transferability.

## 3.1. Conceptual design: select the research method(s)

There are three approaches to theory development, namely a deductive, an inductive, or an abductive approach. the research project will consist of collecting data to explore a phenomenon, namely the development of LA capabilities, and enhance the capability model. The inductive approach will be chosen because this is more in line with the interpretivist research philosophy. Since the capability model will be central to the research project, this research can be classified as exploratory research. This type of research aims to find out what or how the phenomenon of LA capability development works. Exploratory research is a valuable means to ask open questions to discover what is happening and gain insights about a topic of interest (Saunders et al., 2019).

The next methodological choice is the use of a quantitative, qualitative, or mixed methods research design. A qualitative research design is chosen for this research. Qualitative research studies participants meanings and the relationship between them, using a variety of data collection techniques and analytical procedures, to develop a conceptual framework and theoretical contribution (Saunders et al., 2019). Questions, procedures, and focus may alter or emerge during the research process. In this way, the methods used are unstructured or semi-structured. Making use of focus group discussions seems to be the most accurate research strategy. The development of LA capabilities is a phenomenon that will be studied in a higher educational environment. This should be a higher educational institution with some experience with the adoption of LA in their institution. In Appendix 7.4 under case selection a more detailed elaboration of the case selection can be found. Another distinction must be made in the choice to research one or more cases. The objective of this research will be the involvement of three cases. Finally, a time horizon needs to be defined for the research project. In this research, a cross-sectional time frame will be chosen due to the time restriction. Cross-sectional means that a certain snapshot will be taken at a certain time.

## 3.2. Technical design: elaboration of the method

Firstly, some case organizations should be selected to be able to conduct the research. Those organizations should be willing to cooperate in the research project. How these case organizations were approached and contacted is further elaborated in chapter four under research implementation. Further, It could be useful to screen possible cases on their maturity level, to select those cases that have reached an acceptable maturity level. The first aim of the focus groups is the evaluation of the aforementioned capability model. The content and construct validity of this model are checked. Furthermore, it is important to understand whether there is a certain sequence in developing the different capabilities required for LA adoption. The second aim of the focus groups is to examine to what extent the case organization uses a framework such as the implementation timeline for LA adoption, which has been used in the study of Broos et al., (2020). This timeline can act as a methodology to develop the right capabilities at the right time.

The answers that will be sought when conducting the focus groups are the validation of the different LA capabilities with the corresponding operationalizations and whether these have been developed in a certain order when implementing LA in higher education institution. The focus groups will be audio-recorded and transcribed for later analysis. Relevant stakeholders who may be invited to the focus groups include senior management, members of their IT departments, and all those involved in the LA implementation process. The participants in those focus groups should be multidisciplinary. Please note further details on the participants in appendix 7.4. The research could reveal insights into the extent to which the case organizations have paid attention to the development and use of an implementation timeline for LA adoption and the proper order of developing the different capabilities of the relevant educational institution.

## 3.3. Data analysis

Since the research will be qualitative, a corresponding method of analyzing the data will be chosen. Thematic analysis is often seen as a general approach to analyzing qualitative data and can be seen as a fundamental method of analyzing qualitative data (Saunders et al., 2019). The essential purpose of this approach is to look for themes or patterns that occur in a dataset, such as the output of the focus groups. This approach involves the researcher will code the qualitative data to identify themes or patterns for further analysis, related to the central research question (Saunders et al., 2019). This method provides an orderly and logical way to analyse qualitative data.

The procedure of this approach involves four elements: becoming familiar with your data, coding your data, searching for themes and recognising relationships, refining themes, and testing propositions (Saunders et al., 2019). Those four steps as described by Saunders will be followed during the analysis of the qualitative data. Once the output of the focus groups is transcribed each unit of data within a data item will be coded. Two types of coding are applied, namely open coding[11] and axial coding[12]. While reading through the transcripts quotations were placed on participants answers of interest. The five capabilities of the capability model or the four phases of the implementation timeline are potential categories and can be viewed as examples of axial coding, as these are based on knowledge gained from the literature. In Appendix 7.4 under 'Data collection and analysis guidelines' a more detailed elaboration of the data analysis can be found.

## 3.4. Reflection on dependability, credibility & transferability

First of all, it should be mentioned that the domain of learning analytics is still nascent. When carrying out the literature search, the researchers were confronted with the existence of knowledge gaps, precisely because it has not yet been explored and described. This is also often mentioned in the available articles on the subject. The experience in implementing LA at scale in higher education institutions is still very limited today. A low level of experience could be expected in the selection of the case studies that want to participate. This is likely to have implications for the findings that will take place. The above findings also explain why an exploratory research design was chosen. Subsequently, due to the qualitative nature of the design, the study will not be discussed in terms of validity and reliability, but alternative criteria will be used. For qualitative research terms such as dependability, credibility, and transferability are used. Those terms will be explained in the section below.

[11] New codes are formulated when reading the transcripts of the focus group interviews. Those are not based on a priori knowledge.
[12] These codes are structured based on a priori knowledge.

As the focus group discussions will make use of unstructured or semi-structured types of questions there could be concerns about dependability, because of the lack of standardisation in this type of interview. To encounter this concerns the research design, the choice of strategy, methods used, and how the data will be analysed is discussed, so other researchers can undertake similar research. Also, findings derived from explorative research is that these are not necessarily intended to be repeatable since they reflect reality at the time they were collected, in a situation that may be subject to change (Saunders et al., 2019).

There could also be concerns about issues of bias, like interviewer bias[13], interviewee bias[14] and participation bias[15]. To counter these concerns the researchers should be aware of the tone and non-verbal communication used while conducting the focus groups. A neutral attitude is recommended. The answers provided by the participants should represent the complete picture and the researchers should be aware of this, while interpreting them. A high level of credibility can be achieved with the types of focus groups that the research wants to use, when conducted carefully using clarifying questions, probing meanings, and exploring responses from a variety of angles or perspectives (Saunders et al., 2019). Finally, regarding transferability there could be concerns about the use of a small number of cases, but in response to this can the full description of the research questions, design, context, findings, and interpretations allow another researcher to design a similar research project in a different research setting. Further, it is important to recognize that this kind of research is not suitable to make statistical generalizations about an entire population (Saunders et al., 2019).

[13] Comments, tone, and non-verbal behaviour of the interviewer can create bias in the way that interviewees respond to the questions being asked.
[14] This type of bias can be caused by interviewees perceptions about the interviewer, or perceived interviewer bias.
[15] Bias may result from the nature of the individuals or organisational participants who agree to be interviewed.

# 4. Results

In this section, an overview can be found of the design and implementation of the conducted research. Deviations from the initial action plan will be discussed. Also, the outcomes that have been acquired through the research will be presented. The results obtained will be used in the last chapter to discuss, reflect and conclude the findings.

## 4.1. Research implementation

Originally the selection of the case organizations was based on the maturity model of Freitas et al., (2020) as it has been described in the literature review. The experience and contacts of the thesis promotor have been used to be able to get in contact with potential case organizations. In this way, three case organizations were proposed. The three educational institutions that participated in this study will be named HEI1, HEI2, and HEI3. During the focus group discussions, some questions were asked to determine the maturity level of the educational institution. These questions can be found in appendix 4 of the focus group interview protocol, which has been added to appendix 7.5. The participants of this survey for HEI1 and HEI2 answered the questions positively up to the 'structural' maturity level. The third educational institution tends towards the systematic level.

The initial action plan can be found in appendix 7.4. Due to practical reasons, it turned out to be impossible for HEI1 to bring the participants together in a focus group, which is why it was decided to conduct the interviews with the participants separately. Also, the requirement to have four participants in each focus group with an educational, technical, organizational, and operational perspective, as set out in the action plan was not met. Nevertheless, the different focus groups were multidisciplinary in nature and all participants were involved with Learning Analytics or at least student data. In preparation for these meetings, a standard interview protocol was developed that could be used to provide the necessary structure for the focus group discussions. This interview protocol has been slightly adapted to the findings we received from the first interviews. The focus group discussions were semi-structured and therefore mainly consisted of open questions. An example of the latest interview protocol can be found in appendix 7.5.

All transcriptions have been coded by the two researchers by making use of the qualitative research software tool ATLAS.ti. After this coding exercise, both researchers compared their outcomes with each other. As mentioned in the methodology two types of coding were applied, namely open coding and axial coding. While reading through the transcripts quotations were placed on participants answers of interest. The Masterfile contains 245 quotations and 66 codes. An overview of the different code categories and the code distribution by document can be found in appendix 7.6. The axial codes are structured based on a priori knowledge, so they were created before the citation of the transcripts began. These codes are based on knowledge gained from the literature. Within these code categories, second-order capabilities can be found, namely Data, Management, People, Technology, and Privacy & Ethics. The first-order capabilities are the subcodes of these categories. Further, the four phases identified by Broos et al., (2020) were used as axial codes. Finally, also the categories Maturity level and LA expertise are based on a priori knowledge. Once the process of labelling the correct codes to the different quotations was completed the data could be further analysed. With a co-occurrence and a co-document analysing technique, tables were created to explore relations and interesting findings in the data. This will be further elaborated in the following paragraph of this chapter.

## 4.2. Outcomes of the research

The results of the study are presented in this section. More concretely, a generic overview will be given of the various capabilities for each implementation phase. Subsequently, an analysis is described of the similarities and differences of each institution. Towards the end of this section, an attempt is made to further refine the conceptual model.

### 4.2.1. Data Capability category

| | Phase: 1. Initializing phase 76 | Phase: 2. Prototyping phase 30 | Phase: 3. Piloting phase 27 | Phase: 4. Scaling phase 13 |
|---|---|---|---|---|
| Data: Data Usage 7 | 1 (0,01) | 4 (0,12) | | |
| Data: Feedback on analytics 6 | | 2 (0,06) | 3 (0,10) | |
| Data: Quality 7 | 3 (0,04) | 1 (0,03) | 2 (0,06) | |
| Data: Reporting 9 | 2 (0,02) | 4 (0,11) | 2 (0,06) | |
| Data: Sourcing & Integration 5 | 4 (0,05) | | | |

*Table 3: Data capability category by phase*

The capability Feedback on analytics is characterized by quotations that are similarly distributed in the prototyping & piloting phase. The difference in point of view between the various participants mainly lies in whether feedback is already provided during the building process or only after the building process. There appears to be disagreement about the capabilities quality and reporting in that capacity from which phase they are important. For this reason, the respondents answers were examined more deeply. There was a clear difference between HEI1 and HEI3. While HEI1 wants to understand the quality of its data from the start and wants to know what quality is needed before continuing with the process, HEI3 will only think about the quality of its data when they are confronted with it. The opinions of the three HEI are divided on the reporting capability. A participant from HEI3 stated the following, *"From the initialization, there is an intake about what we want to build, to see what type of dashboard & visualisation suits best to display LA."* HEI2 replied that they believe that once you start with dashboarding you will rapidly start prototyping. From the moment you start building something, you will ask the opinion of one another. Finally, a participant from the third educational institution (HEI1) sees reporting mainly from the piloting and scaling phase, because his focus is on existing reports and their maintenance. That means that opinions about certain capabilities can differ because the way something can be viewed can also be different. The following capability category that will be discussed is the Management category.

### 4.2.2. Management Capability Category

| | | Phase: 1. Initializing phase 76 | Phase: 2. Prototyping phase 30 | Phase: 3. Piloting phase 27 | Phase: 4. Scaling phase 13 |
|---|---|---|---|---|---|
| Management: Capability Development | 6 | 3 (0,04) | | 1 (0,03) | |
| Management: Culture & Readiness | 6 | 5 (0,06) | | 1 (0,03) | |
| Management: Evidence-Based & Theory Driven | 5 | 3 (0,04) | | 1 (0,03) | 1 (0,06) |
| Management: External Environment | 6 | 3 (0,04) | | 2 (0,06) | 1 (0,06) |
| Management: Funding & Investment | 6 | 4 (0,05) | 1 (0,03) | | |
| Management: Identifying Benefits | 5 | 5 (0,07) | | | |
| Management: Implementation, Deployment & Application | 6 | 1 (0,01) | 3 (0,09) | 2 (0,06) | |
| Management: Performance Monitoring | 4 | | | 3 (0,11) | 1 (0,06) |
| Management: Policies & CoP | 7 | 4 (0,05) | | | 1 (0,05) |
| Management: Responsibility & Accountability | 5 | 4 (0,05) | | 1 (0,03) | |
| Management: Strategy | 16 | 3 (0,03) | 3 (0,07) | | |

*Table 4: Management capability category by phase*

Generally speaking, the capabilities of the Management capability category are mainly developed in the initialization phase with exceptions for the Implementation, Deployment & Application capability & Performance Monitoring. Participants indicated that the capability Implementation, Deployment & Application knows his development within the prototyping and piloting phase. The capability Performance monitoring shows mainly quotations from the piloting phase. The capability Strategy is characterized by quotations that are similarly distributed in the initialization & prototyping phase. For the External environment capability, disagreement can be noticed between the participants, resulting in a split of quotes between the first and the last two phases. This difference can be explained by the difference in the interpretation of the capability. Both HEI2 and HEI3 believe that this capability has its start of development from the initialization phase. Where participants of HEI1 only recognize the development of this capability from the prototyping phase or even from the scaling phase. At HEI3 there was a participant who quoted it as follows: *"you have to be very clear from the beginning, where your data is going to be used."* At HEI1, on the other hand, they see it more as presenting what has already been achieved to external parties outside the internal organization (for example at conferences) to increase internal interest. For this reason, they only see the importance of this capability in the piloting or even scaling phase. The following capability category is the People category.

### 4.2.3. People Capability Category

| | | Phase: 1. Initializing phase 76 | Phase: 2. Prototyping phase 30 | Phase: 3. Piloting phase 27 | Phase: 4. Scaling phase 13 |
|---|---|---|---|---|---|
| People: Collaboration | 7 | 3 (0,04) | | | 1 (0,05) |
| People: Combined Skills & Knowledge | 6 | 3 (0,04) | 2 (0,06) | | |
| People: Communication | 8 | 3 (0,04) | 2 (0,06) | | 1 (0,05) |
| People: Stakeholder Identification & Engagement | 3 | 3 (0,04) | | | |
| People: Training | 7 | 2 (0,02) | 2 (0,06) | 2 (0,06) | |

*Table 5: People capability category by phase*

Here too it can be said that the capabilities of this capability category are generally developed mainly from the initialization phase. The distribution of the Training capability can be determined over the first three phases. This may be due to an unclear definition of the term training, in particular, that this term can be interpreted broadly. The difference in interpretation here is between training the internal staff to build LA solutions or training the end users to use the LA application. HEI2 and HEI3 refer to *"training on the job"* and *"learning through experience"*, where these two terms refer to internal employees. Whereas HEI1 talks about training for the end users. For them, this is only important in the piloting phase. It can also be noticed that there are still some references to the prototyping phase in the Combined skills & knowledge and Communication capabilities. Such an occurrence can sometimes be because if a capability has its development in the initialization phase, it can also increase in importance in a later phase. The Technology capability category is the next category that will be discussed.

### 4.2.4. Technology Capability Category

| | | Phase: 1. Initializing phase 76 | Phase: 2. Prototyping phase 30 | Phase: 3. Piloting phase 27 | Phase: 4. Scaling phase 13 |
|---|---|---|---|---|---|
| Technology: Automation | 5 | 1 (0,01) | 1 (0,03) | 3 (0,10) | |
| Technology: Connectivity | 6 | 1 (0,01) | | | 3 (0,19) |
| Technology: Infrastructure | 5 | 4 (0,05) | | | |
| Technology: System Characteristics | 4 | 4 (0,05) | | | |

*Table 6: Technology capability category by phase*

Within this category participants agree on the capabilities Infrastructure & System characteristics, they believe that these capabilities are developed from the initialization phase. The Automation capability, on the other hand, is mainly linked to the piloting phase. Although some deviations can be noticed. The answer obtained from HEI3 refers to the application of automation to achieve better data quality. The participant argued to applying automation to the data platform from the initialization phase. Both HEI1 and HEI2 indicate that automation is important in the scaling phase, but that you start working with it from the piloting phase. For both of them, it is about automating the end product to the end users. The participants mainly see the scaling phase as the moment to develop the capability connectivity. In this way, this is the only capability indicated to start developing from the scaling phase. Finally, the last capability category that will be discussed is the Privacy & ethics category.

### 4.2.5. Privacy & Ethics Capability Category

| | | Phase: 1. Initializing phase 76 | Phase: 2. Prototyping phase 30 | Phase: 3. Piloting phase 27 | Phase: 4. Scaling phase 13 |
|---|---|---|---|---|---|
| Privacy & Ethics: Ethics | 7 | 5 (0,06) | | | |
| Privacy & Ethics: Human Decision-Making | 7 | 2 (0,02) | 2 (0,06) | 1 (0,03) | |
| Privacy & Ethics: Legal Compliance | 5 | 4 (0,05) | | | |
| Privacy & Ethics: Security | 7 | 3 (0,04) | 1 (0,03) | | |
| Privacy & Ethics: Transparancy | 7 | 2 (0,02) | 2 (0,06) | 1 (0,03) | |

*Table 7: Privacy & ethics capability category by phase*

More disagreement can be noticed in the Human decision-making and Transparency capabilities, which are divided over the first three phases. Human decision-making may have seemed an unclear capability, as often no or very limited argumentation could be obtained. A participant referred to the fact that decisions are made at a higher level and that such decisions (for example, a change in a curriculum) are not automated. The differences observed for the capability Transparency can be explained by the different angles used to argue this capability. Some interesting statements from HEI1 and HEI3 have been registered. The following answer was obtained from a participant of HEI3 when asked if students are aware of which data fields are used. "*We inform about every category of personal data we are going to use, the source. So if it's from Canvas, from Osiris, the purpose of each personal data that we process, how long we are going to retain it and they also know who is going to access it and why. So I would say from the beginning, because not only do we ask for consent from the students directly, but I do think it's a very transparent process. Very straightforward.*" For a participant of HEI1, the importance of transparency mainly lies in the piloting phase. "*I would especially recommend Transparency from the piloting phase... Because then you really start interacting with end users. And then it is important to communicate transparently and that also depends on your Legal Compliance and Ethics.*" The way a particular capability is viewed or perceived may determine where the participant places the capability on the implementation timeline.

### 4.2.6. Comparison between educational institutions

In the previous analysis, different capabilities were allocated to the implementation phases. Next, further elaboration will take place on how the capabilities are ranked by the different educational institutions. An important note here is that the answers to HEI1 are taken from three separate interviews, these answers were consolidated[16] by making use of the principle "most vote count". In this way, a consolidated result out of these three interviews was obtained. First, a reference is made to the process model as already mentioned in the problem statement. In appendix 7.7 an overview can be found of the conceptual LA capability process model developed by knobbout (2021) and three similar process models that are constructed with the input received from the three educational institutions. The difference between the conceptual process model and the model for each educational institution will be discussed.

In general, for the three educational institutions, it can be concluded that there is a trend in which certain capabilities are shifted to a previous or earlier implementation phase. Furthermore, four capabilities are shifted to the initialization phase by all three educational institutions. These are Sourcing & Integration, Combined skills & Knowledge, Infrastructure, and System characteristics. In addition, all three educational institutions shift four capabilities from the scaling phase to an earlier implementation phase. There are differences between the three HEI about where they finally end up. These capabilities are External environment, Automation, Combined skills & Knowledge, and Training. For some of these capabilities, the answers of the participants have already been discussed, the others will be delineated in more detail. For Combined skills & Knowledge, all participants emphasize more or less the same thing. they point out the importance of paying attention to putting together the right competencies within the team from the start. For Sourcing & Integration it can be argued by a quote from one of the participants of HEI3: "*for any new analytics project, we have an intake checklist. And a part of it is what kind of data are you going to use from which source system is it coming? We need to have it sooner, also for creating a DPIA[17] for instance, and to be privacy compliant*". The capabilities of Infrastructure & System characteristics are perceived as very similar to each other by the participants. The best way to demonstrate their argumentation is using a quote of a participant from HEI3: "*from a technology perspective, we try to adapt that as soon as possible and definitely during*

[16] In appendix 7.7 a detailed excel could be found on this consolidation exercise.
[17] Data protection impact assessment

*initialization I guess because we have a kind of a generic platform, where still some specific components will be used depending on the use case".*

To make it for each HEI more clear at which implementation phase they assigned the different capabilities an IN and OUT map has been constructed. This map shows for each phase which capability comes in and which capability goes out compared to the conceptual process model. This IN and OUT map can be consulted in appendix 7.7. The trend to move capabilities forward one place to an earlier implementation phase can be most strongly observed in HEI1. As a result, the process model still resembles the conceptual one with a wider base and a smaller top. The exceptions to this are culture & readiness, which goes from the piloting phase to the initialization phase, combined skills & knowledge goes from scaling to initialization and implementation, deployment & application is only developed in prototyping, according to HEI1. On Privacy & Ethics, one participant provided a very useful answer, related to the order in which capabilities are developed. The quote was: "*At HEI1 they paid a lot of attention to ethics & privacy in the beginning. They really used a code of practice for that. And it started five years ago. That was really coordinated with the board. How are we going to handle this now? What are we going to do now and what no? What you often see is that people start with data and technology, but then it falls apart, but what you have seen here is that people first really started with the privacy & ethics part and then they took care of management ' buy-in'. This then served as a basis to continue with the data afterward*".

For HEI2 even more capabilities got assigned to the initialization phase, resulting in a smaller prototyping and piloting phase than the conceptual and process model of HEI1. Connectivity remains also here the only capability in the scaling phase. Next to Combined skills & Knowledge also External environment belongs to the initialization phase according to the participants of HEI2. Culture & Readiness, Human Decision making, communication, and training are all three capabilities that are three steps earlier on the implementation timeline compared to the conceptual model. Implementation, Deployment & Application and capability Development are both assigned to the piloting phase, but in the conceptual model, these capabilities were assigned to a earlier phase on the implementation timeline. Here, a quote will be shown about culture & Readiness to better understand why this capability moved forward on the implementation timeline. The participant: "*So basically culture and readiness are what you're doing all the time. Improving and influencing and such. Project leaders are very busy with this and it also involves many different capabilities*".

The downward trend can also be observed in the focus group of HEI3 and it is even striking that a considerable number of capabilities that fell under the scaling phase in the conceptual model have shifted to the initialization phase. Yet at this educational institution, it can also be established that capabilities are moved to a later phase. In this way, Funding & Investment are shifted to the prototyping phase. The capabilities of Quality & Capability development are moved to the piloting phase. Finally, we find Policies & CoP and Performance Monitoring in the scaling phase. The reason why they perceive Performance monitoring from the scaling phase is very clearly stated by one of the participants: "*No, I don't think it's technical. Technical is only facilitating. This capability is about Performance measures. How do we want to measure whether learning analytics is a success or not? Yeah, we didn't think of that so far. I would say after we have a clear strategy and we know how to scale, then it's opportune to measure and see how we are going to perform*".

In what follows, a dimension will be added, namely whether there is consensus between the different educational institutions about which implementation phase can be assigned to a particular capability. In other words, about which capabilities do the educational institutions agree with each other, about which capabilities are there at least agreement between the two of them and are there capabilities about which there is total disagreement? There are 11 capabilities where the three HEI agree on which implementation phase the capability should be assigned. All 11 capabilities are assigned to the initialization phase. Furthermore, there are 17 capabilities on which there is at least agreement between two educational institutions that participated in this study. All four implementation phases are represented in this list. Finally, there are only two capabilities, which the three educational institutions completely disagree on. An overview of the different capabilities within their consensus levels will be presented below.

| Category | Capability | Implementation phase |
|---|---|---|
| Data | Sourcing & Integration | Initialization |
| Management | Identifying benefits | Initialization |
| | Responsibility & Accountability | Initialization |
| People | Combined skills & knowledge | Initialization |
| | Collaboration | Initialization |
| | Stakeholder identification & Engagement | Initialization |
| Privacy & Ethics | Ethics | Initialization |
| | Legal compliance | Initialization |
| | Security | Initialization |
| Technology | Infrastructure | Initialization |
| | System Characteristics | Initialization |

*Table 8: Consensus about capabilities between three educational institutions*

| Category | Capability | Implementation phase | Consensus |
|---|---|---|---|
| Data | Data usage | Prototyping | HEI1 – HEI2 |
| | Quality | Initialization | HEI1 – HEI2 |
| | Feedback on analytics | Piloting | HEI1- HEI3 |
| Management | Capability development | Piloting | HEI2 – HEI3 |
| | Culture & Readiness | Initialization | HEI1 – HEI2 |
| | Evidence-based & Theory driven | Initialization | HEI2 – HEI3 |
| | External Environment | Initialization | HEI2 – HEI3 |
| | Funding & Investment | Initialization | HEI1 – HEI2 |
| | Performance Monitoring | Piloting | HEI1 – HEI2 |
| | Policies & COP | Initialization | HEI1 – HEI2 |
| | Strategy | Initialization | HEI1 – HEI2 |
| | Communication | Initialization | HEI2 – HEI3 |
| | Training | Prototyping | HEI2 – HEI3 |
| Privacy & Ethics | Human decision making | Initialization | HEI2 – HEI3 |
| | Transparency | Initialization | HEI2 – HEI3 |
| Technology | Connectivity | Scaling | HEI1 – HEI2 |
| | Automation | piloting | HEI1 – HEI2 |

*Table 9: Consensus about capabilities between two educational institutions*

| Category | Capability |
|---|---|
| Data | Reporting |
| Management | Implementation, Deployment & Application |

*Table 10: Capabilities without any consensus between three educational institutions*

Some participants shared feedback about the capability Implementation, Deployment & Application, they found the definition rather unclear and some of them even mentioned that this capability could be split into two or three separate capabilities. Perhaps this explains why no consensus was found between the three educational institutions for this capability.

This brings us to the next and also the last angle on the Learning Analytics capability model. In this perspective, the conceptual model is brought together with the findings established during the focus group discussions at the three educational institutions. In this way, we obtain, as it were, a combined LA capability model. In this model, there is consensus for certain capabilities between the conceptual model and the findings conducted at the three educational institutions. These capabilities keep their grey color in the new process model. Concerning these capabilities, it can be said that the findings from the focus group discussions confirm the conceptual model. On the other hand, there are capabilities from the conceptual model, which are not confirmed by the outcome of the three focus group discussions. In other words, these capabilities are given a different place on the implementation timeline when they are tested in practice. These capabilities are given a blue color in the new process model. The presentation of the Learning Analytics Capability Process Model can be found below.

<table>
<tr><th>Initialisation phase</th><th>Prototyping phase</th><th>Piloting phase</th><th>Scaling phase</th></tr>
<tr><td colspan="4">Implementation, Deployment & Application</td></tr>
<tr><td colspan="4">Legal compliance</td></tr>
<tr><td colspan="4">stakeholder Identification & Engagement</td></tr>
<tr><td colspan="4">Collaboration</td></tr>
<tr><td colspan="4">Ethics</td></tr>
<tr><td colspan="4">funding & Investment</td></tr>
<tr><td colspan="4">Identify Benefits</td></tr>
<tr><td colspan="4">Policies & CoP</td></tr>
<tr><td colspan="4">Transparency</td></tr>
<tr><td colspan="4">Security</td></tr>
<tr><td colspan="4">Responsibility & Accountability</td></tr>
<tr><td colspan="4">Strategy</td></tr>
<tr><td colspan="4">Sourcing & Integration</td></tr>
<tr><td colspan="4">Communication</td></tr>
<tr><td colspan="4">Infrastructure</td></tr>
<tr><td colspan="4">System characteristics</td></tr>
<tr><td colspan="4">Evidence-based & Theory-driven</td></tr>
<tr><td colspan="4">Quality</td></tr>
<tr><td colspan="4">Culture & Readiness</td></tr>
<tr><td colspan="4">Combined Skills & Knowledge</td></tr>
<tr><td colspan="4">External Environment</td></tr>
<tr><td colspan="4">Human-decision making</td></tr>
<tr><td></td><td colspan="3">Data Usage</td></tr>
<tr><td></td><td></td><td colspan="2">Performance Monitoring</td></tr>
<tr><td></td><td></td><td colspan="2">Feedback on analytics</td></tr>
<tr><td></td><td></td><td colspan="2">Automation</td></tr>
<tr><td></td><td></td><td colspan="2">Capability Development</td></tr>
<tr><td></td><td></td><td colspan="2">Reporting</td></tr>
<tr><td></td><td></td><td colspan="2">Training</td></tr>
<tr><td></td><td></td><td></td><td>Connectivity</td></tr>
</table>

*Figure 2: Learning Analytics Capability Process Model – For capabilities in grey there is consensus between the conceptual model and the outcome of the three HEI. No consensus was found for the blue capabilities and they represent the outcome of the three HEI.*

# 5. Discussion, conclusions and recommendations

This chapter contains a discussion and reflection on the outcomes of this study. In this discussion, the obtained results are brought in relation to the existing literature. Next, the findings obtained from the results are more concretely concluded. Finally, some recommendations are given for practice and further research.

## 5.1. Discussion – reflection

For practical reasons, HEI1 could not bring all participants together in a focus group at the same time. As a result, three separate interviews were conducted and participants' responses were consolidated afterward. This fact influences the results obtained from the first educational institution. During a focus group, participants can discuss with each other, as well as share insights from a different angle and thus influence the final answer of the focus group. There is therefore a real chance that the results from a focus group would have been different than those from the consolidated variant. These deviating results in turn have an impact on the final conclusions. An example of disagreement between the participants can be found in the capability 'Sourcing & Integration' in the third focus group. One participant disagrees with the proposed phase, while three other participants agree with what is being proposed. This has been made visible in the consensus matrix (Onwuegbuzie et al., 2009), which can be consulted in appendix 7.8.

There are already references in the literature to the sequential adoption of LA. Tsai et al. (2021) propose that first capabilities for contextual factors in data sources, usability, and usefulness must be developed. Second, institutions should focus on people-related issues such as needs, ethics, privacy, communication, capacity, and capability. And third, ethical and privacy issues should be addressed. If these enumerated factors are compared with the capabilities from the LA capability model, then the capabilities of Sourcing & Integration, Identifying benefits, and Data usage can be linked to the contextual factors. Stakeholder identification & Engagement, Identifying benefits and Communication can be bound to the people-related issues. Finally, the ethical and privacy issues can be represented by the capabilities 'Ethics' and 'Security'. In the combined LA capability model these capabilities are represented from the initialization phase, except for Data usage and Capability development. The former knows its development from the prototyping phase, the latter knows its development from the piloting phase.

Adejo and Connolly (2017) explicitly say that sequential adoption is relevant and propose a detailed roadmap with five phases. Some capabilities need to be developed in a particular order. These five phases are the Preliminary phase, Privacy & Compliance, Three integrated roadmaps, Adoption & Evaluation, and finally the Monitoring & Control phase. Also here, a comparison can be made with the capabilities of the LA capability model. The Preliminary phase corresponds with Strategy, Performance monitoring, Data usage, Sourcing & Integration, Stakeholder identification & Engagement, Infrastructure, System characteristics, and Evidence-based & Theory driven. Within the combined LA capability model all these capabilities start from the initialization phase except for Data usage and performance monitoring. The latter knows its development from the piloting phase. Privacy and compliance correspond with the capabilities of Ethics, Legal compliance, Security, Transparency, and Human decision-making. All have their developments in the initialization phase in the LA capability process model. The fourth phase, Adoption and evaluation correspond with the capability Implementation, Deployment & Application, which also starts in the initialization phase. Finally, Monitoring & Control corresponds with the capability Performance monitoring, which knows his development from the piloting phase in the LA capability process model. In a final reference to the literature, one can look at the work of Greller & Drachsler (2012) they say that each category of capabilities must be instantiated to achieve successful learning analytics at an institution. This is in line with our findings in this study, namely that all capability categories are represented in the adoption of LA at the three educational institutions.

During the focus group discussions, feedback was received on the model and methodology used. Several times it was mentioned that the order in which capabilities are developed is not always visible or easy to determine. Comments were received in all focus group discussions about the intensity of working on a particular capability. With this, the participants wanted to make it clear that a capability can develop from the initialization phase, but that the extent to which it continues to develop can differ over the different phases of the implementation timeline. At HEI2, one participant even suggested adding a phase to the implementation timeline. The participant believes that the evaluation of an LA project is underexposed in this way. Precisely because it is so essential that you evaluate it before scaling up. A similar statement was made in the focus group discussion at HEI3. The participant misses the moment or phase when you place certain developments in a production system after you have built them in a development environment. These findings are consistent with the five-step roadmap discussed in the work of Adejo and Connolly (2017). The fourth phase is the adoption & evaluation phase, where these two comments can be placed. In another comment, a participant expressed his indignation that Management support does not constitute a separate capability. Finally, it was emphasized that there is a difference between the stated intentions and how something is implemented in practice. From this, it can be concluded that it is possible to strive for a uniform model, but that the reality is unruly.

The transcripts were coded separately by the two researchers, after which the results were compared. This benefits internal reliability. The unstructured or semi-structured questions are not conducive to reliability. On the other hand, using a focus group interview protocol and applying a whiteboard to interact with the LA capability process model promotes reliability. In qualitative research, this is also called dependability. Concerning the validity of the study, it can be said that only Dutch HEI participated in this study. It means that you cannot generalize the findings to another region, because the educational system or organizational structure & culture etc. may differ. Also, only three HEIs participated, so the results cannot be generalized. In qualitative research, this is also called transferability. Finally, during the focus group discussions, the researchers adopted a neutral attitude with attention to a neutral tone and non-verbal communication to avoid the various forms of bias.

Furthermore, the new LA capability process model should also be viewed with a critical eye. The findings from the HEIs seem to skew the model towards the initialization phase relative to the other phases. Those who think critically may wonder whether it is really necessary to develop all these capabilities from the initialization phase. To answer this, one must look at the definition of the initialization phase and the descriptions and operationalizations of the capabilities. To substantiate this criticism, three capabilities can be considered, namely External environment, communication & Human decision-making. Operationalization of the external environment includes sharing data with other institutions. whether the operationalization of communication consists of communicating information about the developed analytics. Finally, asking oneself what the human role is in the decision process based on the developed analytics is an operationalization of Human-decision making. Whether these capabilities should be addressed at the beginning of the implementation timeline is at least questionable.

Possible causes for this skewed situation could be a misunderstanding of the capability definition and the definition of the implementation phases. Perhaps there is an organizational culture of wanting to plan everything in advance and the aversion to tackling certain things only afterward. The presence of a strong bureaucratic execution process could be another possible cause.

## 5.2. Conclusions

During the focus group discussions, some questions were asked to determine the maturity level of the educational institution. The theoretical description and the survey among the educational institutions to determine to which level of maturity they belong provide an answer to the second research question. Both the first and the second educational institutions seem to belong to the 'structural' level. For HEI3 it can be concluded that the educational institution is between the 'structural' and the 'systematic' level and is the most mature educational institution in the use of Learning Analytics compared to the other two participating organizations.

An important insight that this research yield is the learning analytics capability process model. This model aims to test the theoretical perspective of experts against what is experienced or done in practice. There is consensus for certain capabilities between the conceptual model and the findings conducted at the three educational institutions. These capabilities keep their grey color in the new process model. For other capabilities, no agreement can be established between the conceptual model and the outcomes of the three focus group discussions. These capabilities are given a blue color in the model. In other words, for the capabilities in grey, the conceptual model is confirmed by the findings from the focus group discussions. However, for those in blue, there is no agreement between the conceptual model and the outcomes from the three focus groups. This means that there is more agreement about the capabilities in grey compared to the capabilities in blue. It makes the grey capabilities more reliable than the blue ones. These findings can be viewed in two ways. On the one hand, it is interesting for theoretical experts to note that their conceptual model is not a one-to-one match with what is involved in the adoption of LA in practice. On the other hand, it is important to add some nuance. important here is the understanding of the participants about the concepts used. To what extent did the participants understand the different capabilities and the different implementation phases? For example, the definitions of the capabilities were read at HEI3, but not at HEI1 and HEI2 due to time constraints. However, the lack of a full understanding of these concepts could have a major impact on the outcomes of this study. This suddenly reveals a weakness of this study. In addition, a remarkable conclusion is that for 11 capabilities a consensus has been found between the three educational institutions, which indicates that these capabilities are clear and that the institutions know when these capabilities are developing.

To conclude the third research question a throwback need to be made to the five dimensions that are critical to the success of the organization (Clarck et al, 2020) as described in the theoretical framework. These five dimensions correspond with the capabilities of Quality, Strategy, Policies & CoP, Combined skills & Knowledge, Infrastructure, System characteristics, and Performance monitoring. Looking at the LA capabilities process model, it can be concluded that three capabilities are shaded in grey and are therefore in line with the conceptual model. These are Strategy, Policy & CoP, and Performance Monitoring. The four other capabilities do not fit in with the conceptual model, but are placed in the initialization phase by the educational institutions. This may be an indication that the institutions recognize the importance of these capabilities. In addition, Greller & Drachler (2012) stated that each capability category must be represented to achieve successful adoption of LA at an educational institution. This is also an observation that can be made from the LA capability process model. Each capability category has a representation from the initialization phase. Furthermore, both authors have pointed out the importance of a carefully planned LA implementation to be successful. This is in line with the trend observed at the three educational institutions to develop capabilities from the initialization phase or at least more early on the implementation timeline. Finally, Tsai et al. (2021) state that stakeholder engagement is considered critical to the success of LA deployment. For the Stakeholder Identification and Engagement capability, there was consensus among the three institutions to develop it from the initialization phase.

## 5.3. Recommendations for practice

Based on our research, some recommendations can be made to LA practitioners, senior managers, and educational institutions who are about to implement LA in their institutions. The LA capability process model can serve as a guideline or an example for institutions when they start implementing LA themselves. As an institution, make sure that such implementations are well-prepared. Consider and consult with the stakeholders involved when certain capabilities need to be developed. Allocate the necessary skills & knowledge, when appointing the team. Strive for quality and have a strategy to follow. Base your work on policies and best practices. Start with the elaboration of your Privacy & Ethics regulation and ensure the necessary infrastructure and system properties. Continuously monitor the implementation performance and finally ensure that your stakeholders remain involved. These recommendations are based of the findings on the first and third research questions, namely the order in which LA capabilities should be developed and what capabilities are required for the successful adoption of LA. How this study carried out the maturity analysis at the participating HEI can be applied similarly by other institutions. This will help them decide where they are on the spectrum. In this way, it can be defined which requirements they must subsequently meet to achieve a higher level of maturity.

## 5.4. Recommendations for further research

Conducting this research has helped clarify the topics explored in this study, namely the order in which LA capabilities should be developed, the maturity levels that LA capabilities can have, and what capabilities are required for successful implementation from LA. However, some topics remain underexposed or require further clarification, which makes further research desirable. During the study, some participants shared the same opinion about the difference in intensity when a certain capability is developed or further developed. For example, a certain capability may begin to develop in the initialization phase, but then be further developed in a later phase and with a different degree of intensity. This seems to be an opportunity for further research. But maybe also closely related to this research, what factors ensure that educational institutions clearly show a trend to shift the development of capabilities forward on the implementation timeline? In addition, it is also possible to look further into why the development of a capability can differ between institutions. These differences may depend on the management style, resources used or organisational structure, etc. Finally, further work can of course be done to arrive at a more refined process model, which can guide educational institutions in their learning analytics adoption process.

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# 7. Appendix

## 7.1. Research approach

### 7.1.1. Search query available literature

The literature review is based on the research objective and the sub-questions of the main research question, which was defined in the first chapter. The goal of the literature review is to try to give more insights on those research questions and the review will act as a bridge between the research questions described in the first chapter and the methodology of the research described in the third chapter. A number of terms were listed for each sub-question, which are characteristic of the respective sub-question. In this way, five terms were determined for each sub-question, which were then used in the search query afterwards in the pilot search. The terms used can be found in the table 11.

| Q1 | Q2 | Q3 |
|---|---|---|
| Learning analytics | Learning analytics | Learning Analytics |
| Capabilities | capabilities | capabilities |
| Process Model | maturity level | succesful |
| Adoption | level | success |
| Priorities | adoption level | adoption/implementation |

*Table 11: Overview of terms listed for each sub-question*

A combination of these terms were tested and tried in a pilot search, with not every combination leading to a successful result. By successful is meant that the combination of some terms resulted in zero results, in other words no articles were found. On the other hand it occurred that articles could be found but that there was no selection of a relevant article.

### 7.1.2. Data sources

The Open University digital library[18] was used as a search engine to perform the pilot search. This portal provides access to various databases, which provide access to various literature sources. The pilot search showed that a wide range of articles could be found here. Next to that, the defined search queries were also executed in Google Scholar in order to check if no relevant article was missed. Not all articles were directly accessible on the OU portal. In those cases, the relevant article was looked up in Google Scholar[19] or in a few cases the article was asked for by the author itself. After the pilot search a new search has been conducted taking into account all knowledge and information gathered out of the pilot search and the feedback received on this first search. This search has been conducted on the database of the institute of education sciences[20]. The aim of working with this three different search engine was to avoid missing any relevant article.

[18] https://bibliotheek.ou.nl/
[19] https://scholar.google.nl/
[20] https://eric.ed.gov/

### 7.1.3. Inclusion Criteria

The following inclusion criteria have been applied to improve the quality of the literature, the readability and the limitation of the result:

- Only English literature was allowed
- Newspaper articles, book reviews and theses were excluded for scientific reason
- Only three content types were selected: conference proceedings, publications and journal articles
- Include results from sources other than collection allowed in the library
- All articles are peer-reviewed
- Literature selection: articles are selected on relevance with the research questions

After performing the searches using the various queries, which will be discussed further in detail, the result of the search was screened based on the title and abstract of the concerned literature. Only those articles whose title and abstract showed any relevance to the three sub-questions were selected. Later, those selected articles were screened for relevance on the full article by reading them separately. If it appears that an article is not sufficiently relevant for the sub-questions, it will be removed from the selection.

### 7.1.4. Forward & backward snowballing

The technique of backward snowballing refers to consulting the reference list of a particular article. This technique is used to check which articles were used to write the article. In this way it is possible to find interesting literature sources. In forward snowballing, we look at which articles cite a particular article. In this way, further research of the relevant article can be found. Within this research assignment, these techniques will only be applied to those articles, which can be regarded as a key in formulating an answer to the sub-questions.

## 7.2. Implementation

A number of search queries could be distilled from the above table of terms, which lead to the intended result. The results can be divided per sub-question, but it does not exclude that the articles can be used for the various sub-questions. As already mentioned the research started with a pilot search on the digital OU library and on Google Scholar. The search Query's used in this pilot search are documented first. After knowing about the existence of the institute of education sciences, the Institute's search engine was used to search their database in an additional query. This additional search was conducted to provide a more holistic view of the literature available and to minimize the chance of missing a relevant article. Also the composition of the search queries are slightly different from the pilot search, those query's combine more synonyms of the same terms with the aim of getting more related articles.

<u>Pilot search query's:</u>

Q1:

((TitleCombined:(Learning Analytics)) OR (TitleCombined:(Capabilities))) AND (TitleCombined:(Process model))

((TitleCombined:(Learning Analytics)) OR (TitleCombined:(Capabilities))) AND (TitleCombined:(adoption))

Q2:

((TitleCombined:(Learning Analytics)) OR (TitleCombined:(capabilities))) AND (TitleCombined:(maturity level))

(TitleCombined:(Learning Analytics)) AND ((TitleCombined:(level)) OR (TitleCombined:(capabilities)))

((TitleCombined:(Learning Analytics)) OR (TitleCombined:(capabilities))) AND (TitleCombined:(level))

Q3:

((TitleCombined:(Learning Analytics)) OR (TitleCombined:(Capabilities))) AND (TitleCombined:(Success))

((TitleCombined:(Learning Analytics)) OR (TitleCombined:(Capabilities))) AND (TitleCombined:(Successful))

Additional search query's:

Q1:

learning analytics AND (adoption OR uptake OR implementation) AND (priorities OR Roadmap OR model OR capability OR capacity OR process OR routine)

Q2:

learning analytics AND (adoption OR uptake OR implementation) AND (maturity level OR maturity OR level)

Q3:

learning analytics AND (adoption OR uptake OR implementation) AND (successful OR success)

Running these search queries resulted in the following results table:

| **Search Query: terms** | **Articles found** | **Selected on abstract** | **Selected on full article** |
|---|---|---|---|
| PSQ 1: Learning analytics, capabilities, process model | 121 | 7 | 2 |
| PSQ2: Learning Analytics, capabilities, adoption | 117 | 6 | 5 |
| PSQ3: Learning analytics, capabilities, maturity level | 12 | 3 | 1 |
| PSQ4: Learning analytics, capabilities, level | 28 | 2 | 1 |
| PSQ5: Learning analytics, capabilities, level | 456 | 1 | 1 |
| PSQ6: Learning analytics, capabilities, Success | 204 | 4 | 1 |
| PSQ7: Learning analytics, capabilities, successful | 64 | 3 | 0 |
| ASQ1: Learning analytics, adoption, uptake, implementation, priorities, roadmap, model capability, capacity, process, routine | 80 | 7 | 6 |
| ASQ2: Learning analytics, adoption, uptake, implementation, maturity level, maturity, level | 48 | 1 | 1 |

| | | | |
|---|---|---|---|
| ASQ3: Learning analytics, adoption, uptake, implementation, successful, success | 30 | 0 | 0 |
| Additional literature provided by OU | 7 | | 4 |
| **Total number of articles** | **1160** | **34** | **22** |

*Table 11: Results search query table*

As mentioned above the literature is selected based on the relevance the abstract of the article shows with the predefined research questions. If an abstract was not sufficiently relevant for the sub-questions, the article was not selected. The same criteria was maintained when proofreading the full article. Words like Learning analytics, adoption, implementation, capability, capacity, maturity etc. triggered the attention, but usually the content of the whole abstract was the deciding factor. In a next step, the selected articles were checked for duplicates. It was possible that the same article was selected when the results were screened. Furthermore, the articles handed by the OU were also included in this analysis. In this way an attempt was made to obtain a unique set of articles. This analysis revealed that seven articles were double selected. Four articles are selected from the OU's supplemental literature after reading the full article. This means that the total number of selected articles available for this literature review comes to 22 articles. By reading the full articles, eight articles could be identified as core articles, meaning that those eight articles contain a lot of useful information to describe and answer the predefined research questions.

## 7.3. Theoretical Framework: results

All literature found is documented in a spreadsheet that is included in this appendix by means of various screenshots. This Excel template was used with the aim of keeping track of and documenting all literature and can be found at the end of this section.

The columns that are used to store information related to the articles found are the following:

- ID (unique incremental number)
- Author(s) of the article
- Year of publication
- Title of the article
- Source of the article (medium where it has been published)
- Library where the article has been discovered
- Search Query that has been used
- Relation to sub-question
- Number of citations (optional)
- Duplicates (Y/N)
- Selection by title
- Selection by abstract (Y/N)
- Selection by article (Y/N)
- Remarks
- Forward snowballing (is technique applied on article?)
- Backward snowballing (is technique applied on article?)
- Priority (indicator of how valuable the article is)

The colour code used in the template is just an indication on the research process. The lines in yellow, blue and green are related to the first pilot search, where yellow represents the first research question, blue the second research question and green the third one. The articles in grey are articles that have been provided by the mentor of OU and can not be related to a certain search. The lines in orange are results of the additional search on the ERIC database. Regarding forward and backward snowballing, those techniques are not really applied during the resource process. But the columns are not removed as this is more in line with the initial literature review method. The column Priority has been added in order to be able to filter on certain articles. The values containing this column are 0, 1, 2, 3. The number zero has been applied to the eight core articles as described above. Next to those the articles with an indication of one, followed by articles indicated by two and three. This indication provides information on how valuable the article was to answer on the research questions. Articles with a number three didn't make it for the final literature review selection. Finally, there was also a column indicating the number of citations an article has, but also this has not really been used during the research process.

| ID | Author | Year | Titel | Source | Library | Search Query | Relation to subquestion | # cited | Dublicates | Selection by Titel | Selection by abstract | Selection by article | Remarks |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 2 | Forstner, Eva<br>Kamprath, Nora<br>Röglinger, Maximilian | 2014 | Capability development with process maturity models - Decision framework and economic analysis | Journal of decision systems | https://bibliotheek.ou | | PSQ1 | 1 | N | Y | Y | Y | |
| 8 | Montealegre, Ramiro | 2002 | A Process Model of Capability Development: Lessons from the Electronic Commerce Strategy at Bolsa de Valores de Guayaquil | Organization science (Providence, R.I.) | https://bibliotheek.ou | | PSQ1 | 1 | N | Y | Y | Y | |
| 13 | | 2019 | Learning analytics adoption - approaches and maturity | Society for Learning Analytics Research (SoLAR) | https://bibliotheek.ou | | PSQ2 | 1 | N | Y | Y | Y | |
| 15 | Freitas, Elyda<br>Fonseca, Fernando<br>Garcia, Vinicius<br>Ferreira, Rafael<br>Gasevic, Dragan | 2020 | Towards a Maturity Model for Learning Analytics Adoption An Overview of its Levels and Areas | | https://bibliotheek.ou | | PSQ2 | 2 | N | Y | Y | Y | |
| 16 | Gasevic, Dragan<br>Tsai, Yi-Shan<br>Dawson, Shane<br>Pardo, Abelardo | 2019 | How do we start? An approach to learning analytics adoption in higher education | The international journal of information and learning technology | https://bibliotheek.ou | | PSQ2 | 1 | N | Y | Y | Y | |
| 20 | Knobbout, Justian<br>Van der Stappen, Esther | 2020 | A Capability Model for Learning Analytics Adoption: Identifying Organizational Capabilities from Literature on Learning Analytics, Big Data Analytics, and Business Analytics | International Journal of Learning Analytics and Artificial Intelligence for Education (iJAI) | https://bibliotheek.ou | | PSQ2 | 1 | N | Y | Y | Y | |
| 22 | Rogers Kaliisa, Anders Kluge and Anders I. Mørch | 2021 | Overcoming Challenges to the Adoption of Learning Analytics at the Practitioner Level: A Critical Analysis of 18 Learning Analytics Frameworks | Scandinavian Journal of Educational Research | https://bibliotheek.ou | | PSQ5 | 1 | N | Y | Y | Y | |
| 23 | Tsai, Yi-Shan<br>Kovanović, Vitomir<br>Gašević, Dragan | 2021 | Connecting the dots: An exploratory study on learning analytics adoption factors, experience, and priorities | The Internet and higher education | https://bibliotheek.ou | | PSQ2 | 1 | N | Y | Y | Y | |
| 24 | Al-Ammary, Jaflah<br>Mohammed, Zainab<br>Omran, Fatima | 2016 | E-Learning Capability Maturity Level in Kingdom of Bahrain | TOJET the Turkish online journal of educational technology | https://bibliotheek.ou | | PSQ3 | 2 | N | Y | Y | Y | |
| 28 | Knobbout, Justian | 2020 | Refined definitions of LACM capabilities: Changes made to the definitions of capabilities of the Learning Analytics Capability Model | | https://bibliotheek.ou | | PSQ4 | 2 | N | Y | Y | Y | |
| 31 | Clark, Jo-Anne<br>Liu, Yulin<br>Isaias, Pedro | 2020 | Critical success factors for implementing learning analytics in higher education: A mixed-method inquiry | Australasian Journal of Educational Technology | https://bibliotheek.ou | | PSQ6 | 3 | N | Y | Y | Y | |

*Figure 3: Overview of the first part of the selected literature*

| ID | Author | Year | Titel | Source | Library | Search Query | Relation to subquestion | # cited | Dublicates | Selection by Titel | Selection by abstract | Selection by article | Remarks |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 40 | Joksimovic, Kovanovic & Dawson | 2019 | The Journey of Learning Analytics | HERDSA Review of Higher Education | | AL | | | N | Y | Y | Y | |
| 43 | Van Steenbergen,Bos, Brinkkemper, van de weerd, Bekkers | 2013 | Improving IS Functions Step by Step: The use of focus area maturity models | Scandinavian Journal of Information Systems | | AL | 2 | | N | Y | Y | Y | |
| 45 | Yi-Shan Tsai a,⁎, Diego Rates b, Pedro Manuel Moreno-Marcos c, Pedro J. Muñoz-Merino c, Ioana Jivet d, Maren Scheffel d, Hendrik Drachsler e,d,1, Carlos Delgado Kloos c, Dragan Gašević | 2020 | Learning analytics in European higher education—Trends and barriers | Computers & Education | | AL | | | N | Y | Y | Y | |
| 46 | Justian Knobbout and Esther van der Stappen | 2020 | Where is the Learning in Learning Analytics? A Systematic Literature Review on the Operationalization of Learning-Related Constructs in the Evaluation of Learning Analytics Interventions | IEEE TRANSACTIONS ON LEARNING TECHNOLOGIES | | AL | 1 | | N | Y | Y | Y | |
| 47 | H. McKee | 2017 | An Instructor Learning Analytics Implementation Model | | https://eric.ed.gov/ | ASQ1 | 1 | | N | Y | Y | Y | |
| 49 | T. C. Olugbenga Adejo | 2017 | Learning Analytics in Higher Education Development: A Roadmap | Journal of Education and Practice | https://eric.ed.gov/ | ASQ1 | 1 | | N | Y | Y | Y | |
| 50 | L. P. M. Seyyed Kazem Banihashem | 2021 | Pedagogical Design: Bridging Learning Theory and Learning Analytics | Journal of Learning and technology | https://eric.ed.gov/ | ASQ1 | 1 | | N | Y | Y | Y | |
| 51 | L. P. M. Rebecca Ferguson, Doug Clow, Belinda Tynan, Shirley Alexander, Shane Dawson | 2014 | Setting Learning Analytics in Context: Overcoming the Barriers to Large-Scale Adoption | Journal of Learning Analytics | https://eric.ed.gov/ | ASQ1 | 3 | | N | Y | Y | Y | |
| 52 | P. M. M.-M. Yi-Shan Tsai, Ioana Jivet, Maren Scheffel, Kairit Tammets, Kaire Kollom, Dragan Gašević | 2018 | The SHEILA Framework: Informing Institutional Strategies and Policy Processes of Learning Analytics | Journal of Learning Analytics | https://eric.ed.gov/ | ASQ1 | 1 | | N | Y | Y | Y | |
| 53 | Soo Mang Lim, Simin Ghavifekr, Husaina Banu Kenayathulla | 2021 | optimizing the use of learning analytics through strategic direction and leadership practice: a higher education institution perspective | malaysian online journal of educational sciences | https://eric.ed.gov/ | ASQ2 | 3 | | N | Y | Y | Y | |
| 54 | Broos, Tom Hilliger, Isabel Pérez-Sanagustín, Mar | 2020 | Coordinating learning analytics policymaking and implementation at scale | British Journal of Educational Technology | https://eric.ed.gov/ | ASQ1 | 1 | | N | Y | Y | Y | |

*Figure 4: Overview of the second part of the selected literature*

## 7.4. Focus group protocol

## Introduction

Organizational-broad uptake of learning analytics (LA) requires higher education institutes (HEI) to develop learning analytics-related processes and procedures. Although this is not a new insight, the institutional adoption of learning analytics remains quite immature (Colvin et al., 2015). The research of Colvin et al. takes a system dynamics view and suggest that long-term learning analytics adoption depends on mutually influencing resources and assets, whilst two key capabilities – strategic and implementation capabilities – are drivers for pushing educators from 'interested' to 'implementing'.

Recently a new capability model has been designed by Knobbout and his colleagues (2020). The objective of this research is to reach a better understanding of the already designed capability model and how it could be enhanced in order to facilitate the adoption of learning analytics at higher educational institutions. This capability model can be classified as an input model. Transforming this input model into a process model would be beneficial as process models are more able to capture the complexity of HEI instead of input models (Broos et al., 2020). Since a process model considers implementation as an iterative and continuous process, it is able to capture mentioned complexity.

For the purpose of allocating resources in order to reach a certain maturity level of a capability, it would be beneficial to know which capability needs to be developed and in what order (Knobbout, 2021). The main objective of this research is to get a better sight on which capabilities are needed at what time when implementing LA at a HEI.

Many learning analytics research is done in Anglo-Saxon countries. However, educational systems vary between countries and research outcomes are therefore heavily contextual. In this study we will therefore focus on Dutch higher educational institutes in particular and research in what order capabilities are needed to build to successfully apply learning analytics. This is done via a case study, in which we research the capabilities of institutes which are mature in the application of learning analytics.

## Theoretical background

Over the years several models have been developed to overcome implementation challenges and support the adoption of LA. In the literature three kinds of models can be found, those are input, output and process models (Broos et al., 2020). Input models focus on the dimensions needed for LA adoption. An Output model focuses on the dimensions and what outcomes to expect from it. Finally, the process models are starting from a serial of processes in order to achieve LA adoption. An overview of the strengths and weaknesses of the different model types can be found in below table.

| Model type | Strengths | Weaknesses |
|---|---|---|
| Input | - A quick insight into what dimensions are important<br>- Consider a variety of dimensions, not only data/technology | - Unclear how to be operationalized<br>- Little attention for interaction between dimensions<br>- Often abstract and generic |
| Output | - Considers the desired outcomes<br>- Map development over time | - Barely addresses the complexity of implementation<br>- Do not deliver specific guidelines |
| Process | - View implementation as an iterative and continuous process | - Empirical validation is yet low<br>- No practical guidelines on how to be operationalized |

| | | |
|---|---|---|
| | - Capable of dealing with the complexity of implementation | |

*Table 12: Comparison of existing models*

Recently a new capability model has been designed by Knobbout and his colleagues (2020). This model pays attention to what resource-based capabilities are necessary for the adoption of LA and how to operationalize these capabilities (Knobbout et al, 2020). This capability model can be classified as an input model. A graphical representation of the model can be found below.

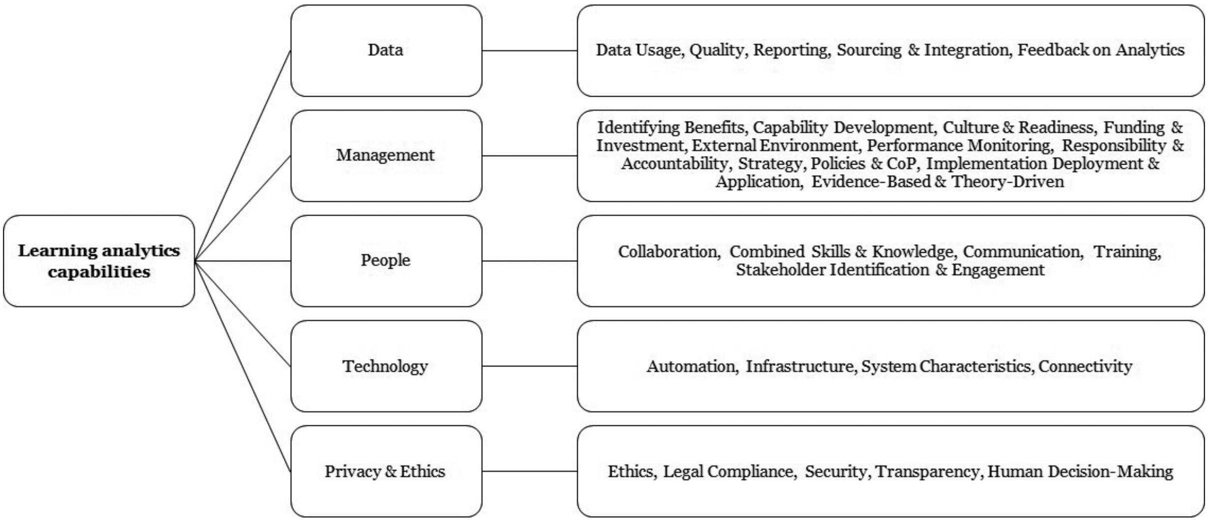


*Figure 5: Capability model for LA (Knobbout et al., 2020)*

More research is needed towards the process behind the adoption of LA at HEI. During the implementation process it is likely that there will some capabilities that need development at the start of the process, while other capabilities are more necessary at the end of it. For the purpose of allocating resources in order to reach a certain maturity level of a capability, it would be beneficial to know which capability needs to be developed and in what order (Knobbout, 2021).

With the intention of exploring the order in which capabilities are developed, the study by Adejo & connolly (2017) was examined in more detail. This study provides a roadmap that can be used in the implementation of LA at the institutional level. The roadmap consist out of five phases: preliminary planning phase; security, privacy and compliance phase; roadmap development phase; adoption an evaluation phase and the monitoring and control phase (Adejo & connolly, 2017).

In the study of Broos et al., (2020) a similar implementation timeline has been used to orchestrate the interaction between policy making and implementation. This implementation timeline can be used as an additional guidance for LA implementations at scale. The timeline consists four phases: first an initialization phase, followed by a prototyping phase, a piloting phase and finally a scaling phase (Broos et al., 2020).

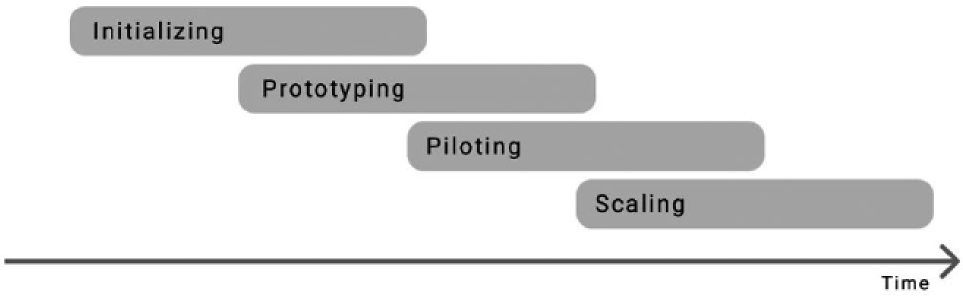


*Figure 6: Implementation timeline*

During the research the implementation timeline of Broos et al. (2020) will be used as this is a more recent developed version of a timeline that could be used when implementing LA. Also has this timeline already been discovered during the promotion research of the tutor involved.

The purpose of conducting the focus groups is to think out loud of a new theoretical model. Which capabilities can be assigned to which implementation phase. Assigning the development of the capabilities to the different phases will let us move from an input model towards a process model for LA adoption.

The objective of the case study at hand is of exploratory nature. That is, based on qualitative data from cases with a certain degree of learning analytics maturity. The main research question is formulated as follows: "*In what order and at what level should educational institutions develop learning analytics capabilities to successfully deploy LA?*" The main research question can be divided in three sub questions:

1. *In what order should LA capabilities be developed?*
2. *What are the different maturity levels LA capabilities can have?*
3. *What capabilities are required for the successful adoption of LA?*

# Case selection

During the case study, we will investigate multiple cases. That is, we consider each higher education institute a specific case with its own learning analytics capabilities. The unit of analysis is the group of stakeholders involved in learning analytics activities, who will be invited to participate in the case study. The case selection strategy is as follows. First, we need to select proper cases, i.e., higher education institutes in the Netherlands. To identify learning analytics capabilities, the institutes need a certain degree of analytics maturity. Based on the maturity model of Davenport, Harris & Morison (2010), the following inclusion criteria are used to select cases:

- The institute uses learning analytics to improve learning and the environment in which this learning takes place;
- The institute started to create centralized data repositories, for example Learner Records Stores (LRS);
- The institute shows early stages of institute-broad application of learning analytics;
- The importance of learning analytics is recognized by institutional leaders of the institute;
- Analysts working at learning analytics are grouped in key target areas;
- The institute is located in the Netherlands.

In the Netherlands, there are 55 governmental financed higher educational institutes (NVAO, 2018[21]). However, not all of these institutes deploy learning analytics activities, and only a few are mature at it. The Special Interest Group Learning Analytics (SIG LA) of SURFnet[22] is formed by experts in learning analytics from different Dutch higher educational institutes. As first step in our selection process, we ask these experts which institutes they believe to meet the inclusion criteria and why. To verify whether a case meets the inclusion criteria, an evaluating conversation with a contact person is held. See Appendix A: Letter to initial contact persons for a letter to contact persons who we already know and are familiar with our research. If the inclusion criteria are met, the organization can be used as case in the study at hand.

Second, when the case organizations are known, the participants for the focus groups must be selected. We opt for focus groups as they allow for the extraction of implicit, abstract and perhaps subconscious knowledge from the focus group subjects. Learning analytics is a multidisciplinary field including "educators, learning scientists, computer scientists, administrators, and policy makers" (Suthers & Verbert, 2013, p. 2) and consequently, the focus groups need to reflect this. Based on the framework of Cosic, Shanks & Maynard (2015), focus group subjects must be involved in the areas *governance*, *people*, *technique* and *culture*. The latter, however, we expect to be experienced by all focus group subjects and we therefore do not seek for experts in that particular area. To summarize, we propose to interview experts and practitioners with the following characteristics from each institute:

- An expert on the educational part of learning analytics (*education)*. For instance, someone who is familiar with the educational or pedagogical effects of learning analytics at the institute like a course designer who uses learning analytics to improve existing courses or design new ones based on insights gained from data.
- An expert on the technical side of learning analytics (*technology*). For instance, the administrator of the Learner Record Store or a data/IT-infrastructure architect.
- An expert on the institute's policy or strategic implementation regarding learning analytics (*governance)*. For instance, an administrator or a policy maker.
- A practitioner who uses learning analytics to improve learning or the surroundings where the learning takes place (*people)*. For instance, a lecturer or academic advisor.

So, for each of the cases, we will have focus groups with four stakeholders. The contact persons of each case organization are asked to provide names of people who have extensive knowledge of one of the above described areas. This way, we get a homogenous group of experts over all cases (Figure 3). The subject's expertise will be checked in the invitation letter – see Appendix B: Letter to potential interview subjects

[21] https://www.nvao.net/samenwerkingstudenten/hoger-onderwijs-nederland
[22] Collaborative organization for ICT in Dutch education and research

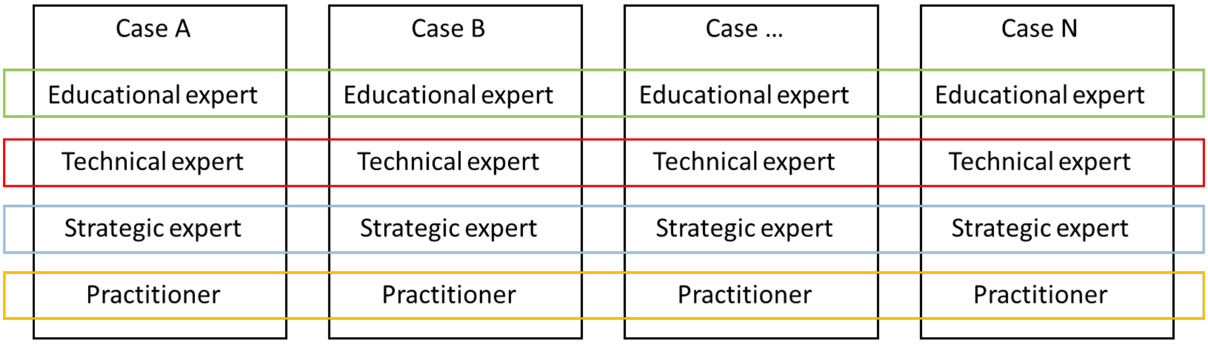


*Figure 7: Distribution of Expertise Over Cases.*

## Data collection and analysis guidelines

Data will be collected during focus groups. To ensure the quality of our work, we will use other data sources as well. That is, next to the data collected during the focus groups, we will also analyze documentation from the institutes related to the topics we are interested in. This includes learning analytics policies, documents related to learning analytics infrastructure, internal learning analytics usage guidelines et cetera.

As suggested by Runeson & Höst (2009, p. 151), the data collection and analysis will partly be carried out in parallel. This way, insights gained from the analysis can lead to the refinement of research instruments like the focus group interview scheme. After each focus group, the results are analyzed in order to refine the instruments. The processing of the cases will be done sequential, i.e., case for case.

During the focus groups, notes will be taken to follow up on interesting topics mentioned by the focus group subjects later on in the conversation. Moreover, each focus group session will be recorded. The recordings will be used to transcribe the entire focus group interview. The transcription is then send to the focus group subjects, who then "has the chance to point out if he or she does not agree with the interpretation of what was said or if he or she simply has changed his or her mind and wants to rephrase any part of the answers" – the member check (Runeson & Höst, 2009, p. 146). The transcriptions will then be coded and analyzed.

Focus group subjects are asked for formal organizational documentation (policies, [internal] research papers et cetera) related to their work. The documents are processed in a same matter as the focus group interview transcripts. This way, we include multiple sources of data into our research, thus enhancing its quality by multi-source data. As it involves explicit information, there is no need for a member check as the subject's opinion will not influence the documents' content.

As for the coding process, an approach as described by Strauss & Corbin (1990) is proposed. This approach comprises of three steps: 1) open coding, 2) axial coding, and 3) selective coding. In the first step, codes are created by analyzing the data. When reading the transcripts of the focus group interviews, some topics may already stand out based on a priori knowledge. To process the rest of the transcripts, on the other hand, new codes need to be formulated. The open coding is followed by axial coding, where the codes are structured based on existing knowledge (see Figure 4). Finally, in the step of selective coding, themes are identified within the output of the axial coding.

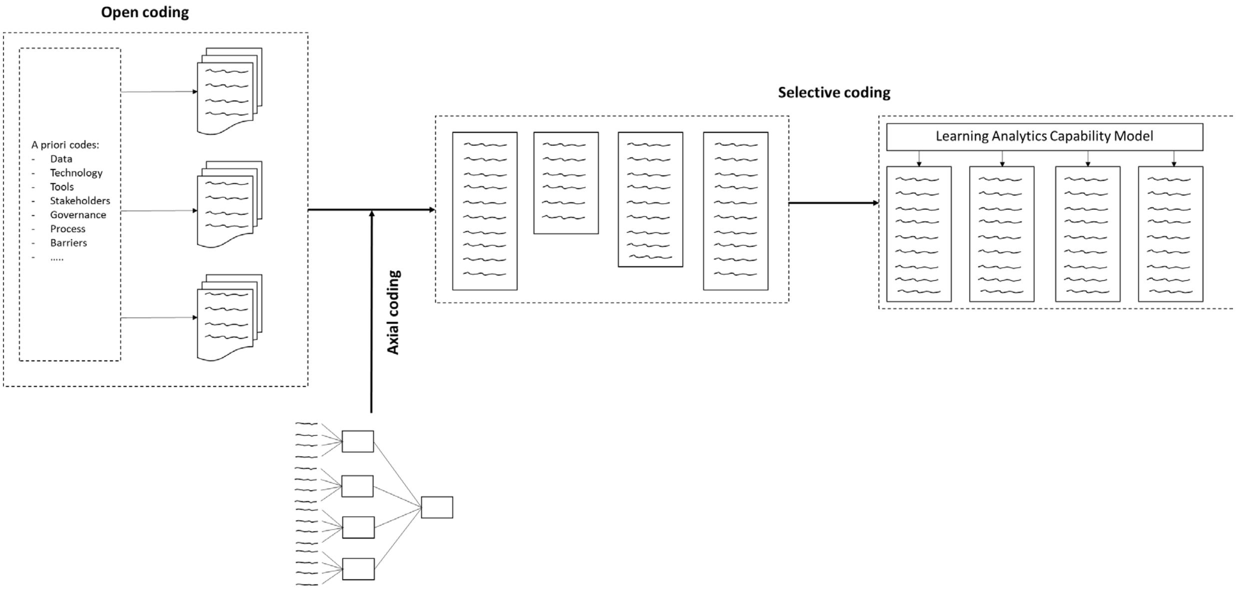


*Figure 8: Coding Process of the Case Study.*

# Planning

A case study involves five major process steps (Runeson & Höst, 2009, p. 137), which we use to make a planning for our study:

- Case study design: May and June 2022.
- Preparation for data collection: September and October 2022.
- Collecting evidence: October and November 2022.
- Analysis of collected data: October and November 2022.
- Reporting: November and December 2022 and January 2023.

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# Appendix A: Letter to initial contact persons

Beste [naam],

Het uitvoeren van een case study maakt onderdeel uit van mijn scriptieonderzoek. In deze case study zullen personen van verschillende functies die betrokken zijn bij de uitvoer van learning analytics binnen hun onderwijsinstelling geïnterviewd worden. Tijdens het interview wil ik ingaan op de voor learning analytics benodigde organisatorische *capabilities* (processen, routines) en hoe die zijn ingericht binnen de instelling. Omdat [naam instelling] al een zekere mate van volwassenheid rondom learning analytics kent, zou ik graag personen uit deze organisatie spreken. Omdat ik niet precies weet wie binnen [naam instelling] ik het beste kan benaderen, vraag ik je om hulp. Zou je mij kunnen introduceren met, of wellicht de contactgegevens kunnen geven van, personen die binnen jouw organisatie bezig zijn met:

- De educatieve kant van learning analytics, bijvoorbeeld onderwijskundigen of cursusontwikkelaars die data gebruiken om beter onderwijs te ontwerpen;
- De technische kant van learning analytics, bijvoorbeeld beheerders van jullie LRS of (data) infrastructuurarchitecten;
- De organisatorische kant van learning analytics, bijvoorbeeld beleidsmedewerkers;
- De uitvoerende kant van learning analytics, bijvoorbeeld docenten of studieloopbaanbegeleiders die learning analytics actief gebruiken binnen hun onderwijs/begeleiding.

Per case binnen mijn onderzoek probeer ik met minstens één persoon per bovenstaand gebied te spreken. Mocht je meerdere personen per gebied weten, dan houd ik mij uiteraard aanbevolen. Het interview zal ongeveer een uur in beslag nemen en op locatie worden uitgevoerd in de periode september tot november 2022.

Ik hoop dat je me kunt helpen met het vinden van de juiste personen binnen [naam instelling]. Alvast hartelijk bedankt.

# Appendix B: Letter to potential interview subjects

Beste,

Via [naam contactpersoon] kreeg ik je contactgegevens door. Ik ben student aan de Open Universiteit en doe mijn scriptieonderzoek naar de toepassing van Learning Analytics. Mijn onderzoek vertrekt uit het reeds ontwikkelde Capability model. Hierover willen we onderzoeken of de capabilities in een wel bepaalde volgorde ontwikkeld worden. Van [naam contactpersoon] begreep ik dat jij je bezighoudt met [deelgebied]. Ik zou je graag een interview afnemen om te bespreken hoe dit binnen [naam instelling] wordt toegepast. De resultaten van het interview worden meegenomen binnen de analyse van mijn scriptieonderzoek. Zou het mogelijk zijn om ergens in [maand] hiervoor een uur in te plannen? Voorstel zou zijn om dit interview in [plaats] te laten plaatsvinden.

Mocht je niet in de gelegenheid zijn om mij te spreken, zou je mij misschien willen doorverwijzen naar iemand binnen [instelling] die zich ook met [deelgebied] en learning analytics bezighoudt?

Alvast bedankt.

## 7.5. Focus Group Interview Protocol

**Interview protocol learning analytics capability model**

***In advance (0 min tot 5 min) - Jens***

1. Is there any objection to recording the interview? This is purely necessary for the transcription of the interview. We will also share the transcript for an agreement.
    a. No objection? Then start recording. Test whether sound and video are working properly.
2. About the interview
    a. Interview is semi-structured, we go through different questions together.
    b. You don't have to know all the terms that come up, but feel free to ask.

***Introduction (5 min tot 10 min) - Jens***

3. Jens and Linda introduce themselves
    a. Master Business Process Management & IT
    b. Thesis about sequence in the learning analytics capability model for successful adoption by higher educational institutions, explanation will follow
4. Participant introduces him/herself
    a. Name, profession
    b. Experience with learning analytics
        i. The manner in which
        ii. How many years by TU/e
        iii. How many years in that function?
        iv. How many years working experience with learning analytics?
5. Who can we contact to talk /email about the state of maturity? It is a short simple questionnaire.

***Learning analytics / study data capability's (10 min – 20 min) - Linda***

6. *Show the Learning Analytics Capability Model (zie bijlage 2, without sequence) on the screen.*
7. What you see is the learning analytics capability model.
    a. Capabilities are the ability that an organization possesses or can develop to achieve a specific goal or outcome. This often involves a combination of different resources to achieve a result.
    b. For example, for the capability 'reporting', employees can apply certain knowledge and use systems to generate useful reports on the use of learning analytics.

10. Do you recognize the capabilities? Which (categories) do? Which not?
11. Can you tell us something about the sequence between these different capabilities? How did that happen with the adoption of learning analytics / study data within your educational institution?

***Sequence Phases (20 min – 30 min) - Linda***

12. There are several ways to look at sequence. In our thesis we follow the model of Broos. This distinguishes between four different phases.
    a. phase 1 – initialisation

        i. In the first phase, it is important to create a common understanding of the issues that will be addressed and the basic needs of the LA project. A project team must be assembled and an overview-level schedule must be defined..
   b. phase 2 – prototyping
        i. Typical activities include prototyping and consulting with various stakeholders to identify requirements and validate design choices and assumptions. The prototypes are used as a tool to support their design activities, discussion and improvement through iteration.
   c. phase 3 - Piloting
        i. This phase focuses on testing the solution design in a natural environment. It is about using real data and real users in a context that is representative of the intended purpose of the solution. Only a subset of the intended user population is targeted.
   d. phase 4 - Scaling
        i. The final phase builds on what has been learned from the previous phases to re-implement or at least redeploy the intended solution on a large scale. This is where the entire population is targeted: all targeted courses, programs, and faculties.
13. Are the phases recognizable for your educational institution?
   e. If yes, in what way?
   f. If not, is there another structure that can be applied within the educational institution?

***Feedback on the LACM with sequence (30 min – 55 min) - Linda***

*14.* In this model, the LACM and the sequence of Broos are combined. Now we are happy to walk this model with you, from top to bottom. Which positioning do you agree with? And with what not?
15. Are you still missing capabilities? If yes which one?

***Additional questions (when time available) – Jens and Linda***

16. What does sequentially mean within the capability model according to you?
17. What is the importance of the sequence of those different capabilities?
18. Can a capability belong to different phases in your opinion? If yes which one?
19. Can there be sequence between the different capabilities within a particular phase? If so? What does it look like then??
20. Which capabilities are certainly important in the initial phase? Which ones certainly have an interest in the final phase?
21. Which capabilities do you think belong to different phases? Which do you think belong to only one phase?
22. Bijlage 4

***closing (55 min – 60 min) - Linda***

23. Thanks a lot!
24. We will share a transcript of the interview, if you have any feedback on this, we'd love to hear it.

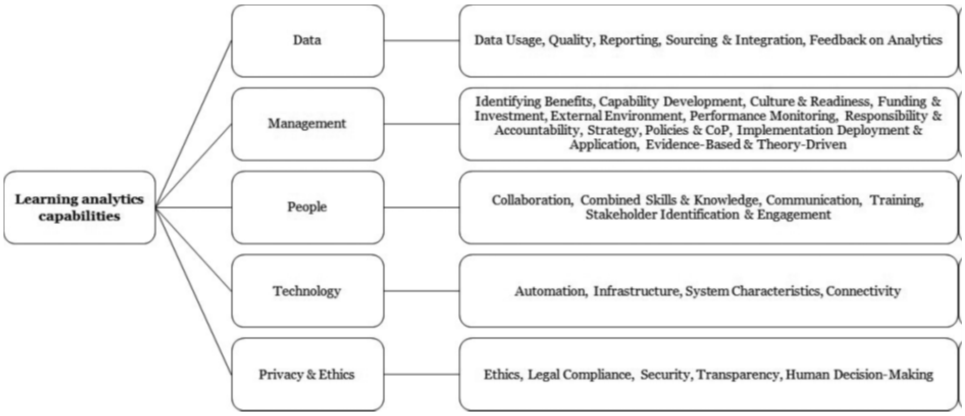
25. Of course we will also share our final result (two theses) with you, and Justin Knobbout will continue with the results within the LA working group of SURF, among others..

**Bijlage 1**

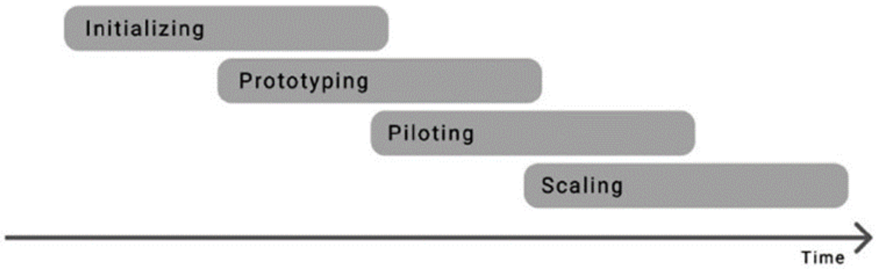
1. Ad Hoc:
   On this level, an institution is beginning the Learning Analytics adoption. In general, projects take place through initiatives of individual stakeholders (e.g., professors, researchers, or educational designers), and it involves a small group of students. There are no formal established processes, and the projects occur without prior planning of the objectives to be achieved by using LA; it happens only by using the tools available within the institution, publically available or developed by the individual who leads the initiative;
2. Initial:
   On this level, Learning Analytics is also adopted in other departments of the institution, with greater stakeholder involvement, such as professors and students, and under the informal leadership of one or more researchers. Since the tools are already in use, they can be evaluated and enhanced through user feedback. The expected results when achieving this level are:
    a. more extensive coverage of LA projects, resulting in a higher quantity of users and, consequently, more data to be analyzed, which can generate more mature LA solutions;
    b. greater engagement and understanding of the role of LA in different departments of the institution;
    c. regulations defined by the institution protects students' privacy; and
    d. initial initiatives aiming at training teachers and students for using LA tools;
3. Structured:
   This level is characterized by senior management involvement in the Learning Analytics adoption processes, as the benefits resulting from its use have become visible. The institution can define goals to be achieved by using LA, and the development of new tools is aligned with these goals. There is an increase in the complexity level of the developed tools and the evaluation of these tools. This level of maturity requires a more robust infrastructure. There are a formally established leadership and working team responsible for the projects' success. The benefits on this level of maturity include:
    a. formation of leadership and working group leads to a coordinated project execution, and thus, increases the probability of success;
    b. more attention to the infrastructure to support LA projects and solutions is provided; and
    c. aligning solutions with the institution's priorities helps reinforce the senior management commitment to sponsorship and success of LA projects; and
4. Systematic:
   On this level, LA becomes institutionalized. There is funding committed to existing and new projects, which now involve professionals from different fields of knowledge. Solutions become increasingly effective in meeting the priorities of the institution and even the priorities of relevant stakeholders. The LA leader has the autonomy to decision making, and the results obtained by adopting LA are disseminated throughout the institution, helping to minimize any problems of resistance to changes. Benefits of achieving this level include:
    a. solutions can be enriched by the background of professionals from different fields of knowledge;

b. LA becomes part of the institutional culture, and it is included in the Strategic Planning; and
c. institution has processes, people, and goals for using LA

**Bijlage 2:**




**Bijlage 3:**




**Bijlage 4:**

***Maturity learning analytics / study data***

8. We would first like to find out about the maturity of the use of learning analytics / study data within your educational institution. For this we have some questions that we need a short answer to.
    a. Ad Hoc
        i. Are there formal projects with planning and structure around learning analytics / study data? The manner in which? Or are these projects still unstructured?
    b. Initial
        i. Is learning analytics / study data used in multiple places within the educational institution? How far does this go?
    c. Structured
        i. Have strategic goals been set within the educational institution with a role for learning analytics / study data?
        ii. Is senior management at the educational institution involved in the adoption / implementation of learning analytics / study data?
        iii. Are there multiple applications in use for learning analytics / study data? And are they integrated with each other?

d. Systematic
   i. Does learning analytics / study data play a role in strategic planning within the educational institution?
   ii. Is there one person responsible for learning analytics / study data within the educational institution with the autonomy to determine a direction for the entire institution?
   iii. Are there employees from different knowledge areas involved in the ongoing LA projects?

## 7.6. Open & Axial coding

| Name | Grounded |
|---|---|
| Context | 22 |
| Data | 30 |
| LA expertise | 13 |
| Management | 67 |
| Maturity Level | 29 |
| Other codes | 68 |
| People | 30 |
| Phase | 139 |
| Privacy & Ethics | 24 |
| Technology | 19 |

*Figure 9: Code Categories*

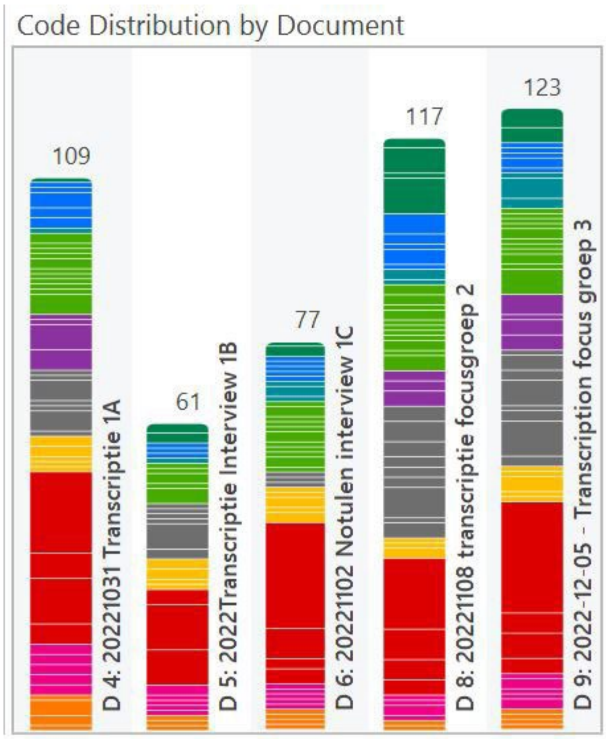



*Figure 10: Code distribution by document*

## 7.7. Learning Analytics Process Model

| Capability | Original | Interview 1a | Interview 1b | Interview 1c | Consolidated 1abc | Comment 1abc | Focusgroup 2 | Consolidated 1 + 2 | Comment 1+2 | Focusgroup 3 | Consolidated 1+ 2+ 3 | Comment 1+ 2+ 3 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Quality | 2 | 1 | | 1 | 1 | | 1 | 1 | | 3 | ? | |
| Sourcing & Integration | 2 | 1 | | 1 | 1 | | 1 | 1 | | 1 | 1 | |
| Data Usage | 3 | 2 | | 2 | 2 | | 2 | 2 | | 1 | ? | |
| Reporting | 3 | | | 2 | 3 | | 2 | 2 | | 1 | ? | |
| Feedback on analytics | 3 | 2 | | | 3 | | 2 | 2 | | 3 | ? | |
| Identifying benefits | 1 | | | | 1 | | 1 | 1 | | 1 | 1 | |
| Funding & Investment | 1 | | | | 1 | | 1 | 1 | | 2 | ? | |
| Responsibility & Accountability | 1 | 3 | | | 1 | Larger deveation | 1 | 1 | | 1 | 1 | |
| Strategy | 1 | | 2 | | 1 | | 1 | 1 | | 2 | ? | |
| Policies & CoP | 1 | | | | 1 | | 1 | 1 | | 4 | ? | |
| Implementation Deployment & Application | 1 | 3 | 2 | 2 | 2 | | 3 | 3 | ! Consolidated value is higher than original and first value | 1 | ? | |
| Capability Development | 2 | 1 | | 1 | 1 | | 3 | 3 | ! Consolidated value is higher than original and first value !! Larger devation between 1abc and 2 | 3 | ? | |
| Evidence-Based & Theory-Driven | 2 | 4 | 3 | 1 | 2 | No majority, hence the original value | 1 | 1 | | 1 | ? | |
| Culture & Readiness | 3 | 1 | | 1 | 1 | Larger devation | 1 | 1 | | 3 | ? | |
| Performance Monitoring | 3 | 4 | | | 3 | | 3 | 3 | | 4 | ? | |
| External Environment | 4 | 3 | 3 | | 3 | | 1 | 1 | is lower than original and first value !! larger devation between 1abc and 2 | 1 | ? | |
| Collaboration | 1 | | | | 1 | | 1 | 1 | | 1 | 1 | |
| Stakeholder Identification & Engagement | 1 | 2 | | | 1 | | 1 | 1 | | 1 | 1 | |
| Communication | 3 | 2 | 2 | 4 | 2 | Larger devation | 1 | 1 | | 1 | ? | |
| Combined Skills & Knowledge | 4 | 1 | 2 | 1 | 1 | | 1 | 1 | | 1 | 1 | |
| Training | 4 | 3 | 3 | 1 | 3 | Larger devation | 2 | 2 | | 2 | ? | |
| Infrastructure | 2 | 1 | | 1 | 1 | | 1 | 1 | | 1 | 1 | |
| System Characteristics | 2 | 1 | | 1 | 1 | | 1 | 1 | | 1 | 1 | |
| Automation | 4 | 3 | 3 | 2 | 3 | | 3 | 3 | | 1 | ? | |
| Connectivity | 4 | 4,5 | | | 4 | | 4 | 4 | | 1 | ? | |
| Ethics | 1 | | | | 1 | | 1 | 1 | | 1 | 1 | |
| Legal Compliance | 1 | | | | 1 | | 1 | 1 | | 1 | 1 | |
| Security | 1 | | 2 | | 1 | | 1 | 1 | | 1 | 1 | |
| Transparency | 1 | 3 | 2 | 2 | 2 | | 1 | 1 | | 1 | ? | |
| Human Decision-Making | 3 | 2 | | 2 | 2 | | 1 | 1 | | 1 | ? | |

*Figure 11: LA Process model based on interviews*

<table>
<tr><th>Initialisation phase</th><th>Prototyping phase</th><th>Piloting phase</th><th>Scaling phase</th></tr>
<tr><td colspan="4">Implementation, Deployment & Application</td></tr>
<tr><td colspan="4">Legal compliance</td></tr>
<tr><td colspan="4">stakeholder Identification & Engagement</td></tr>
<tr><td colspan="4">Collaboration</td></tr>
<tr><td colspan="4">Ethics</td></tr>
<tr><td colspan="4">funding & Investment</td></tr>
<tr><td colspan="4">Identify Benefits</td></tr>
<tr><td colspan="4">Policies & CoP</td></tr>
<tr><td colspan="4">Transparency</td></tr>
<tr><td colspan="4">Security</td></tr>
<tr><td colspan="4">Responsibility & Accountability</td></tr>
<tr><td colspan="4">Strategy</td></tr>
<tr><td></td><td colspan="3">Sourcing & Integration</td></tr>
<tr><td></td><td colspan="3">Capability Development</td></tr>
<tr><td></td><td colspan="3">Infrastructure</td></tr>
<tr><td></td><td colspan="3">System characteristics</td></tr>
<tr><td></td><td colspan="3">Evidence-based & Theory-driven</td></tr>
<tr><td></td><td colspan="3">Quality</td></tr>
<tr><td></td><td></td><td colspan="2">Culture & Readiness</td></tr>
<tr><td></td><td></td><td colspan="2">Data Usage</td></tr>
<tr><td></td><td></td><td colspan="2">Communication</td></tr>
<tr><td></td><td></td><td colspan="2">Performance Monitoring</td></tr>
<tr><td></td><td></td><td colspan="2">Reporting</td></tr>
<tr><td></td><td></td><td colspan="2">Human-decision making</td></tr>
<tr><td></td><td></td><td colspan="2">Feedback on analytics</td></tr>
<tr><td></td><td></td><td></td><td>Automation</td></tr>
<tr><td></td><td></td><td></td><td>Combined Skills & Knowledge</td></tr>
<tr><td></td><td></td><td></td><td>External Environment</td></tr>
<tr><td></td><td></td><td></td><td>Training</td></tr>
<tr><td></td><td></td><td></td><td>Connectivity</td></tr>
</table>

*Figure 12: Conceptual LA process model (knobbaut, 2021)*

<table>
<tr><th>Initialisation phase</th><th>Prototyping phase</th><th>Piloting phase</th><th>Scaling phase</th></tr>
<tr><td colspan="4">Combined Skills & Knowledge</td></tr>
<tr><td colspan="4">Legal compliance</td></tr>
<tr><td colspan="4">stakeholder Identification & Engagement</td></tr>
<tr><td colspan="4">Collaboration</td></tr>
<tr><td colspan="4">Ethics</td></tr>
<tr><td colspan="4">funding & Investment</td></tr>
<tr><td colspan="4">Identify Benefits</td></tr>
<tr><td colspan="4">Policies & CoP</td></tr>
<tr><td colspan="4">Quality</td></tr>
<tr><td colspan="4">Security</td></tr>
<tr><td colspan="4">Responsibility & Accountability</td></tr>
<tr><td colspan="4">Strategy</td></tr>
<tr><td colspan="4">Sourcing & Integration</td></tr>
<tr><td colspan="4">Capability Development</td></tr>
<tr><td colspan="4">Infrastructure</td></tr>
<tr><td colspan="4">System characteristics</td></tr>
<tr><td colspan="4">Culture & Readiness</td></tr>
<tr><td></td><td colspan="3">Transparency</td></tr>
<tr><td></td><td colspan="3">Implementation, Deployment & Application</td></tr>
<tr><td></td><td colspan="3">Data Usage</td></tr>
<tr><td></td><td colspan="3">Communication</td></tr>
<tr><td></td><td colspan="3">Evidence-based & Theory-driven</td></tr>
<tr><td></td><td colspan="3">Human-decision making</td></tr>
<tr><td></td><td></td><td colspan="2">Performance Monitoring</td></tr>
<tr><td></td><td></td><td colspan="2">Feedback on analytics</td></tr>
<tr><td></td><td></td><td colspan="2">Automation</td></tr>
<tr><td></td><td></td><td colspan="2">Reporting</td></tr>
<tr><td></td><td></td><td colspan="2">External Environment</td></tr>
<tr><td></td><td></td><td colspan="2">Training</td></tr>
<tr><td></td><td></td><td></td><td>Connectivity</td></tr>
</table>

*Figure 13: LA process model for focus group 1*

**Focus Group 1:**

*Initialization*

| IN: | | OUT: | |
|---|---|---|---|
| | Quality | | Implementation, Deployment & Application |
| | Sourcing & Integration | | Transparency |
| | Capability development | | |
| | Culture & Readiness | | |
| | Combined skills & knowledge | | |
| | Infrastructure | | |
| | System Characteristics | | |

*Prototyping*

| IN: | | OUT: | |
|---|---|---|---|
| | Data Usage | | Quality |
| | Implementation, Deployment & Application | | Sourcing & Integration |
| | Communication | | Capability Development |
| | Transparency | | Infrastructure |
| | Human Decision Making | | System characteristics |

*Piloting*

| IN: | | OUT: | |
|---|---|---|---|
| | External Environment | | Data Usage |
| | Training | | Culture & Readiness |
| | Automation | | Communication |
| | | | Human Decision making |

*Scaling*

| IN: | | OUT: | |
|---|---|---|---|
| | | | External Environment |
| | | | Automation |
| | | | Combined skills & knowledge |
| | | | Training |

*Figure 14: IN & OUT analyse focus group 1*

<table>
<tr><th>Initialisation phase</th><th>Prototyping phase</th><th>Piloting phase</th><th>Scaling phase</th></tr>
<tr><td colspan="4">Combined Skills & Knowledge</td></tr>
<tr><td colspan="4">Legal compliance</td></tr>
<tr><td colspan="4">stakeholder Identification & Engagement</td></tr>
<tr><td colspan="4">Collaboration</td></tr>
<tr><td colspan="4">Ethics</td></tr>
<tr><td colspan="4">funding & Investment</td></tr>
<tr><td colspan="4">Identify Benefits</td></tr>
<tr><td colspan="4">Policies & CoP</td></tr>
<tr><td colspan="4">Quality</td></tr>
<tr><td colspan="4">Security</td></tr>
<tr><td colspan="4">Responsibility & Accountability</td></tr>
<tr><td colspan="4">Strategy</td></tr>
<tr><td colspan="4">Sourcing & Integration</td></tr>
<tr><td colspan="4">Communication</td></tr>
<tr><td colspan="4">Infrastructure</td></tr>
<tr><td colspan="4">System characteristics</td></tr>
<tr><td colspan="4">Culture & Readiness</td></tr>
<tr><td colspan="4">Evidence-based & Theory-driven</td></tr>
<tr><td colspan="4">Human-decision making</td></tr>
<tr><td colspan="4">Transparency</td></tr>
<tr><td colspan="4">External Environment</td></tr>
<tr><td></td><td colspan="3">Data Usage</td></tr>
<tr><td></td><td colspan="3">Reporting</td></tr>
<tr><td></td><td colspan="3">Training</td></tr>
<tr><td></td><td colspan="3">Feedback on analytics</td></tr>
<tr><td></td><td></td><td colspan="2">Automation</td></tr>
<tr><td></td><td></td><td colspan="2">Performance Monitoring</td></tr>
<tr><td></td><td></td><td colspan="2">Implementation, Deployment & Application</td></tr>
<tr><td></td><td></td><td colspan="2">Capability Development</td></tr>
<tr><td></td><td></td><td></td><td>Connectivity</td></tr>
</table>

*Figure 15: LA process model for focus group 2*

**Focus Group 2:**

*Initialization*

| | IN | OUT |
|---|---|---|
| Initialization | Quality<br>Sourcing & Integration<br>Evidence-Based & Theory Driven<br>Culture & Readiness<br>External Environment<br>Communication<br>Combined skills & Knowledge<br>Infrastructure<br>System Characteristics<br>Human Decision making | Implementation, Deployment & Application |
| Prototyping | Data Usage<br>Reporting<br>Feedback on analytics<br>Training | Quality<br>Sourcing & Integration<br>Capability Development<br>Evidence-Based & Theory driven<br>Infrastructure<br>System characteristics |
| Piloting | Implementation, Deployment & Application<br>Capability Development<br>Automation | Data Usage<br>Reporting<br>Feedback on analytics<br>Culture & Readiness<br>Communication<br>Human Decision making |
| Scaling | | External Environment<br>Automation<br>Combined skills & knowledge<br>Training |

*Figure 16: IN & OUT analyse focus group 2*

<table>
<tr><th>Initialisation phase</th><th>Prototyping phase</th><th>Piloting phase</th><th>Scaling phase</th></tr>
<tr><td colspan="4">Combined Skills & Knowledge</td></tr>
<tr><td colspan="4">Legal compliance</td></tr>
<tr><td colspan="4">stakeholder Identification & Engagement</td></tr>
<tr><td colspan="4">Collaboration</td></tr>
<tr><td colspan="4">Ethics</td></tr>
<tr><td colspan="4">Data Usage</td></tr>
<tr><td colspan="4">Identify Benefits</td></tr>
<tr><td colspan="4">Connectivity</td></tr>
<tr><td colspan="4">Reporting</td></tr>
<tr><td colspan="4">Security</td></tr>
<tr><td colspan="4">Responsibility & Accountability</td></tr>
<tr><td colspan="4">Automation</td></tr>
<tr><td colspan="4">Sourcing & Integration</td></tr>
<tr><td colspan="4">Communication</td></tr>
<tr><td colspan="4">Infrastructure</td></tr>
<tr><td colspan="4">System characteristics</td></tr>
<tr><td colspan="4">Implementation, Deployment & Application</td></tr>
<tr><td colspan="4">Evidence-based & Theory-driven</td></tr>
<tr><td colspan="4">Human-decision making</td></tr>
<tr><td colspan="4">Transparency</td></tr>
<tr><td colspan="4">External Environment</td></tr>
<tr><td></td><td colspan="3">funding & Investment</td></tr>
<tr><td></td><td colspan="3">Strategy</td></tr>
<tr><td></td><td colspan="3">Training</td></tr>
<tr><td></td><td></td><td colspan="2">Quality</td></tr>
<tr><td></td><td></td><td colspan="2">Culture & Readiness</td></tr>
<tr><td></td><td></td><td colspan="2">Feedback on analytics</td></tr>
<tr><td></td><td></td><td colspan="2">Capability Development</td></tr>
<tr><td></td><td></td><td></td><td>Performance Monitoring</td></tr>
<tr><td></td><td></td><td></td><td>Policies & CoP</td></tr>
</table>

*Figure 17: LA process model for focus group 3*

**Focus Group 3:**

*Initialization*

IN: Sourcing & Integration
Data Usage
Reporting
Evidence-Based Theory
External Environment
Communication
Combined skills & Knowledge
Infrastructure
System Characteristics
Automation
Connectivity
Human Decision making

OUT: Funding & Investment
Strategy
Policies & CoP

*Prototyping*

IN: Funding & Investment
Strategy
Training

OUT: Quality
Sourcing & Integration
Capability Development
Evidence-Based & Theory driven
Infrastructure
System characteristics

*Piloting*

IN: Quality
Capability Development

OUT: Data Usage
Reporting
Performance Monioring
Communication
Human Decision making

*Scaling*

IN: Policies & CoP
Performance Monitoring

OUT: External Environment
Automation
Combined skills & knowledge
Training
Connectivity

*Figure 18: IN & OUT analyse focus group 3*

## 7.8. Consensus Matrix Analysis

| Capability | Member 2A | Member 2B | Member 2C |
|---|---|---|---|
| Data Usage | SD | NR | NR/D |
| Feedback on analytics | SE | D | NR |
| Quality | NR | NR | A |
| Reporting | NR | D | D |
| Sourcing & Integration | NR | NR | A |
| Capability Development | NR/D | NR | NR/D |
| Culture & Readiness | A | A | A |
| Evidence-based & Theory driven | D | D | NR |
| External environment | D | D | D |
| Funding & Investment | NR | A | NR |
| Identifying benefits | NR | A | A |
| Implementation, Deployment & Applicatior | NR | SD | SD |
| Performance Monitoring | NR | A | SD |
| Policies & CoP | A | A | A |
| Responsibility & Accountability | NR | A | A |
| Strategy | NR | A | A |
| Collaboration | NR | NR | NR |
| Stakeholder identification & Engagement | NR | NR | NR |
| Communication | NR | NR | D |
| Combined Skills & Knowledge | NR | NR | NR |
| Training | D | D | D |
| Infrastructure | NR | NR | NR |
| System Characteristics | NR | NR | NR |
| Automation | NR | A | NR |
| connectivity | A | NR | A |
| Ethics | NR | NR | NR |
| legal compliance | NR | NR | NR |
| Security | NR | NR | NR |
| Transparency | NR | D | D |
| Human Decision-Making | NR | D | D |

Legend:

| | |
|---|---|
| A | Indicated agreement with proposed phase |
| D | Indicated dissent with proposed phase |
| SE | Provided siginificant statement or example suggesting agreement |
| SD | Provided siginificant statement or example suggesting dissent |
| NR | Did not indicate agreement or dissent (nonresponse) |
| NR/D | Did not indicate agreement or dissent (doubt) |

*Figure 19: Consensus matrix for focus group 2*

| Capability | Member 3A | Member 3B | Member 3C | Member 3D | Member 3E | Member 3F |
|---|---|---|---|---|---|---|
| Data Usage | NR | D | NR | NR | SD | NR |
| Feedback on analytics | SD | NR | NR | NR | SD | NR |
| Quality | NR | NR | SD | NR | D | NR |
| Reporting | NR | NR | NR | NR | D | NR |
| Sourcing & Integration | A | NR | A | NR | A | SD |
| Capability Development | NR | NR | NR | NR | D | NR |
| Culture & Readiness | NR | NR | NR | NR | D | NR |
| Evidence-based & Theory driven | NR | NR | SE | NR | SE | NR |
| External environment | NR | NR | NR | NR | A | NR |
| Funding & Investment | SD | NR | NR/D | NR | NR/D | NR |
| Identifying benefits | A | A | A | NR | A | NR |
| Implementation, Deployment & Applicatior | NR/D | NR | NR | NR | NR/D | NR |
| Performance Monitoring | NR/D | NR | NR/D | NR | NR/D | NR/D |
| Policies & CoP | SD | NR | SD | NR | SD | NR |
| Responsibility & Accountability | NR | A | A | NR | NR | NR |
| Strategy | SD | NR | SD | NR | D | NR |
| Collaboration | NR | NR | A | NR | A | NR |
| Stakeholder identification & Engagement | NR | NR | SE | NR | A | NR |
| Communication | NR/D | A | NR | NR | A | NR |
| Combined Skills & Knowledge | NR | NR | NR | NR | A | A |
| Training | NR | SD | NR/D | NR | A | SD |
| Infrastructure | NR | NR | NR | NR | A | A |
| System Characteristics | NR | NR | NR | NR | NR | A |
| Automation | NR | NR | SD | NR | NR | D |
| connectivity | NR | NR | NR | NR | NR | D |
| Ethics | NR | NR | A | NR | A | NR |
| legal compliance | NR | A | NR | NR | A | NR |
| Security | NR | NR | A | NR | NR | NR |
| Transparency | NR | A | NR | NR | NR | NR |
| Human Decision-Making | NR | A | SE | NR | A | NR |

Legend:

| | |
|---|---|
| A | Indicated agreement with proposed phase |
| D | Indicated dissent with proposed phase |
| SE | Provided siginificant statement or example suggesting agreement |
| SD | Provided siginificant statement or example suggesting dissent |
| NR | Did not indicate agreement or dissent (nonresponse) |
| NR/D | Did not indicate agreement or dissent (doubt) |

*Figure 20: Consensus matrix for focus group 3*