A Capability Model for Learning Analytics Adoption

Identifying Organizational Capabilities from Literature on Learning Analytics, Big Data Analytics, and Business Analytics

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Abstract—Despite the promises of learning analytics and the existence of several learning analytics implementation frameworks, the large-scale adoption of learning analytics within higher educational institutions remains low. Extant frameworks either focus on a specific element of learning analytics implementation, for example, policy or privacy, or lack operationalization of the organizational capabilities necessary for successful deployment. Therefore, this literature review addresses the research question "*What capabilities for the successful adoption of learning analytics can be identified in existing literature on big data analytics, business analytics, and learning analytics?"* Our research is grounded in resource-based view theory and we extend the scope beyond the field of learning analytics and include capability frameworks for the more mature research fields of big data analytics and business analytics. This paper's contribution is twofold: 1) it provides a literature review on known capabilities for big data analytics, business analytics, and learning analytics and 2) it introduces a capability model to support the implementation and uptake of learning analytics. During our study, we identified and analyzed 15 key studies. By synthesizing the results, we found 34 organizational capabilities important to the adoption of analytical activities within an institution and provide 461 ways to operationalize these capabilities. Five categories of capabilities can be distinguished – *Data, Management, People, Technology*, and *Privacy & Ethics.* Capabilities presently absent from existing learning analytics frameworks concern *sourcing and integration, market, knowledge, training, automation,* and *connectivity*. Based on the results of the review, we present the Learning Analytics Capability Model: a model that provides senior management and policymakers with concrete operationalizations to build the necessary capabilities for successful learning analytics adoption.

Keywords—Learning analytics, capabilities, adoption, big data analytics, business analytics, resource-based view

1 Introduction

Learning analytics aim at optimizing learning and the environment in which learning occurs by analyzing and intervening on learner-generated data [1]. Although the results show promising effects, much learning analytics practice in the past decade is done at a small scale with a limited number of students and teachers involved. As a result, examples of the large-scaled application within higher educational institutions remain scarce. Learning analytics can bring competitive advantages to the educational domain, but to do so, institutions must invest in resources and institutional capacities [2]. This investment requires strategic planning at the highest level of the institution. To address the strategic investment higher educational institutions need to make, we take the lens of the resource-based view theory as our main perspective. The resource-based view has been used to study, among others, big data analytics and business analytics – two research fields similar to learning analytics. Hence, we consider it useful to the learning analytics community and use this theory to study learning analytics adoption.

This study aims to identify organizational capabilities for large-scale implementation and adoption of learning analytics in higher educational institutions. As we want to aggregate the findings of prior studies to develop a new model, we conduct a literature review. Therefore, our paper has two main contributions to the research field. The first is a literature review on the commonalities and differences between capabilities for business analytics, big data analytics, and learning analytics. The second is a capability model to support the implementation and uptake of learning analytics. We enhance the current body of knowledge by not only providing an overview of important capabilities but also their operationalization. This important aspect is often overlooked in existing models on learning analytics implementation. Moreover, rather than limiting ourselves to the field of learning analytics, in our search we include literature from research fields with a longer history of using data to enhance processes and the environment in which these processes take place. In contrast to existing models, we take a comprehensive look at the implementation and adoption rather than only a specific part of it like privacy and ethics (e.g. [3]–[5]) or policy (e.g., [6], [7]). Finally, to the best of our knowledge, we are the first ones who use the resource-based view to study learning analytics. The review provides an answer to the main research question: "*What capabilities for the successful adoption of learning analytics can be identified in existing literature on big data, business and learning analytics?*"

The remainder of this paper is structured as follows. First, we provide an overview of the background of the study. We will then describe in detail the methodology we applied, after which we present the results of our study. Finally, in the discussion section, we provide recommendations for future work, including the planned approach for refinement and validation of the Learning Analytics Capability Model and as well as a discussion on the limitations of our study. The complete set of ways to operationalize the learning analytics capabilities is published online[1].

2 Theoretical Background

In this section, we start with an overview of known problems faced by higher educational institutions when trying to adopt learning analytics at scale. We then describe

[1]https://www.researchgate.net/publication/339847879_Learning_Analytics_Capability_Model

some of the known frameworks supporting the uptake of learning analytics by higher educational institutions. Finally, we elaborate on the resource-based view.

2.1 Learning analytics adoption challenges and frameworks

Much research focusses on the application of learning analytics in a limited context [8]. As a result, the institutional adoption of learning analytics and embedding in educational systems remains quite immature [9]–[11]. A systematic literature review by Viberg et al. [12] on the use of learning analytics in higher education shows that 94% of the studies described in the reviewed papers (n=252) does not scale. A reason for this might be that higher educational institutions scaling up on learning analytics face a variety of problems and challenges, e.g., issues with usability, access, performance, and calculation [13], concerns about privacy and ethics [14], lack of exemplars and guiding resources as well as technical, social, and cultural issues [15], or proving the value of learning analytics, aligning it with learning sciences, and collecting useful data in a secure way [16]. In a review of extant literature, Tsai & Gašević [17] identified six primary challenges related to strategic planning and learning analytics policies, including a shortage of leadership capabilities and insufficient training opportunities for end-users. Empirical research by Ifentaler & Yau [18] shows that stakeholders often can identify the resources necessary for learning analytics adoption but that most institutions still need to build and attain these required resources.

The issues and challenges withholding higher educational institutes to adopt learning analytics successfully attract the attention of scholars. Noticeable studies on the subject of learning analytics implementation are the Europe-oriented Supporting Higher Education to Integrate Learning Analytics (SHEILA) framework [7] and its Latin American counterpart, the LALA framework [19]. Both frameworks can be used to inform strategic planning and policy processes for large-scale implementation in higher education contexts. The SHEILA framework's focus is on policy development and comprises six dimensions, each containing three key elements. Although questions in the framework prompt answers and actions which help institutions to mitigate challenges, policies do not necessarily provide direct solutions to the identified challenges [7]. The LALA framework, which is highly influenced by the SHEILA framework, is composed of four fundamental dimensions [20]. The framework is yet grounded in theory and empirical validation is suggested as future work. Nonetheless, preliminary results show that there is no such thing as "one-size-fits-all" for large-scale learning analytics adoption, as institutional needs differ per university. During a literature review, Colvin et al. [21] identified nine different frameworks to support learning analytics implementation. From their analysis, it can be learned that five dimensions are considered to impact implementations: technological readiness, leadership, organizational culture, staff and institutional capacity, and learning analytics strategy. However, the authors state that "operationalizations of these dimensions varied across the literature" ([21], p. 285).

To the best of our knowledge, there is no literature review conducted to identify and analyze the different ways organizational capabilities supporting the adoption of learning analytics are operationalized. Our study aims to fill this knowledge gap. Successful adoption is not only about possessing the right resources (e.g., hardware, software, skilled people) but also about the ways these resources are deployed and managed. This is best described by the resource-based view, which we introduce in the next paragraph.

2.2 Resource-based view

The resource-based view attributes organizational performance to its resources, which, to obtain sustained competitive advantages, must be valuable, rare, inimitable, and non-substitutable [22], [23]. They are generally divided into categories as financial resources, physical resources, human resources, technological resources, organizational resources, and reputation [22], [24]. Resources relate to assets and capabilities [25], [26]. Assets involve anything which can be deployed by organizations to create, produce and offer its goods or services to a market and can be either be tangible, intangible or personnel-based [23]. Capabilities, on the other hand, are repeatable patterns of actions in the use of these assets [25]. They involve "complex patterns of coordination between people and between people and other resources" ([24], p. 122) and are essentially interacting routines. Capabilities are a special kind of resource since they refer to an organization's capacity to deploy other resources and ownership cannot be transferred between organizations. Capabilities are strongly "embedded in the organization and its processes" ([27], p. 388) and cannot easily be bought, but need to be built in order to effectively interact with the organizational processes and procedures.

To research what capabilities are necessary for learning analytics, we turn to two adjacent research fields: big data analytics and business analytics. With ever-growing datasets - both in size and complexity - big data analytics provides the required knowledge about "advanced and unique data storage, management, analysis, and visualization technologies" to handle these datasets ([28], p. 1166). Business analytics, on the other hand, analyze data to understand and manage businesses more effectively [29] and is parallel to analytics in an educational setting [30]. The resource-based view has been used to study capabilities for big data analytics and business analytics in the past [31].

As the field of learning analytics is younger than big data analytics and business analytics, we choose to apply exaptation. Exaptation is the process of extending known solutions in one domain to solve problems in another domain [32]. These solutions have a high degree of maturity in one domain but the application maturity in the focal domain is yet low. Consequently, prior ideas need to be tested and refined, resulting in opportunities for research and knowledge contribution. Although learning analytics have a specific goal – improve learning and learning environments – the goals and intents of analytics at the institutional level are similar for organizations in the educational domain and those in other domains. Therefore, in our research, we not only look at learning analytics literature but include studies from big data analytics and business analytics as well.

3 Methodology

In this study, we will answer the main research question: "What capabilities for the successful adoption of learning analytics can be identified in existing literature on big data analytics, business analytics, and learning analytics?" The following sub-questions operationalize the main research question:

RQ1: "What capabilities necessary for the successful adoption of big data analytics and business analytics within an organization can be identified in existing literature?"

RQ2: "What capabilities necessary for the successful adoption of learning analytics within a higher educational institution can be identified in existing literature?"

RQ3: "Which similarities and differences can be identified between capabilities for big data analytics and business analytics, and learning analytics?"

Fig 1 shows the relationship between the main research question, the sub-questions and the final outcome of the study: the Learning Analytics Capability Model.

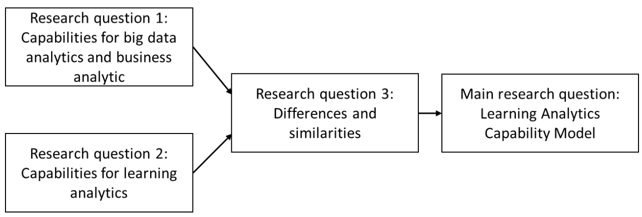

Fig. 1. Relationship between the main research question and sub-questions.

3.1 Method for RQ1

Much research towards the required capabilities for big data analytics and business analytics has already been performed. Adrian et al. [31] have conducted a systematic literature review to investigate factors and elements affecting big data analytics implementation while taking a resource-based perspective. The authors identified 15 key studies, which we will initially include in our research. As we also want to include literature on business analytics capabilities and are interested in the way capabilities can be operationalized, we conduct an additional literature review. We are particularly looking for papers developing capability frameworks, for these extensively describe both capabilities and their operationalization. As we want to include literature from many different domains, we use Google Scholar as search engine. We use the following search string: *("big data analytics capabilities" OR "big data analytics capability" OR "business analytics capabilities" OR "business analytics capability" OR "BA capability" OR "BDA capability" OR "BA capabilities" OR "BDA capabilities") AND ("resource-based view")*. To select key studies for analysis, we apply the inclusion and exclusion criteria shown in Table 1.

Table 1. Inclusion and exclusion criteria.

Criterion	Inclusion	Exclusion
Language	English	Non-English
Outlet	Peer-reviewed conference proceeding papers or journal papers	Book (chapters), master thesis, editorial comments
Framework	Research on big data analytics and business analytics capability frameworks	Research on individual capabilities or anecdotal research findings
Operationalization	Provides a description of the operationalization of capabilities	No operationalization provided
Validation	Empirically validated frameworks	No validation
Citations	Cited by others at least once	Not cited by others
No follow-up	Newly identified framework	Follow-up studies using already identified framework

Based on titles and abstracts, papers not meeting our selection criteria are removed from the dataset. Next, by reading the full texts of the remaining papers, key studies are identified. From the key studies, the operationalizations of analytical capabilities are extracted and coded based on open coding principles. In open coding, items are compared with each other for similarities and then labeled, allowing conceptually similar items to be grouped to form categories [33]. Capabilities can variate in level, resulting in a hierarchical order [34]. In our study, we distinguish between third-order, second-order, first-order, and zero-order capabilities. Third-order capabilities are the highest level and describe the core concept. Second-order capabilities describe the different categories of capabilities within the core concept. First-order capabilities describe the abilities necessary to achieve individual tasks. Finally, zero-order capabilities are the ways first-order capabilities are operationalized – Fig 2. This leveling will be used to structure the outcomes of our literature review. Based on similarity, we group operationalizations into first-order capabilities, which in turn are categorized into second-order capabilities. To secure the quality of the coding process, all coding is done by two researchers in parallel. The results are compared and any differences are discussed until consensus is reached.

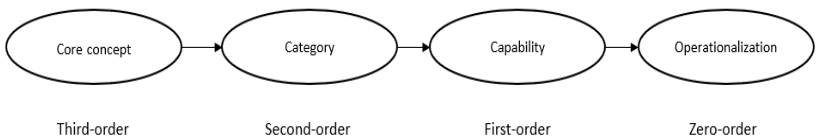

Fig. 2. Hierarchical order of various levels of capabilities.

3.2 Method for RQ2

In a recent review of existing literature on learning analytics deployment, Colvin et al. [21] identified a dozen learning analytics implementation models. We take this study as the starting point for our second research question and include the 12 studies in our search process. To make sure no relevant models are missed, we perform an additional search in two major databases in which, among others, papers from the Journal of

Learning Analytics and the Learning Analytics and Knowledge (LAK) conference proceedings papers are published: Education Resources Information Center (ERIC) and Association for Computing Machinery (ACM). We use the search string *"learning analytics" AND (adoption OR uptake OR implementation) AND (capability OR capacity OR process OR routine OR asset OR "resource-based view")* for both databases. On the models identified by Colvin et al. and the papers we found during the additional search, the same criteria as for research question 1 are applied (Table 1) with only one exception. Instead of describing research on big data analytics and business analytics capability frameworks, papers must describe research on learning analytics implementation, adoption, and/or use at scale. Titles and abstracts are scanned to remove papers clearly not meeting the inclusion criteria. The final selection of key studies will be made by thoroughly reading the full texts of the remaining papers and comparing them with the selection criteria.

In the first round of coding, the operationalizations extracted from the key studies are coded based on the a priori coding scheme: the outcomes of research question 1. That is, the capabilities defined in that part of our study are used to identify similar capabilities in the learning analytics frameworks. Concepts not relating to any of these capabilities are then coded based on open coding principles [33]. This way, we can identify capabilities and operationalizations unique for learning analytics compared to big data analytics and business analytics. Similar to the coding process for the first research question, the coding will be done by two researchers who code, compare and discuss all capabilities found during the search.

3.3 Method for RQ3

The first two research questions lead to data on the capabilities for either big data analytics and business analytics or learning analytics. In the third research question, differences and similarities between the different fields are analyzed. By plotting the number of operationalizations instances per category, we will show which categories are predominantly present in one field or the other. Next, by considering each category individually, remarkable (dis)similarities will be identified and presented.

4 Results

In this section, we will elaborate on the results of our research per research question. First, we will describe the big data analytics and business analytics capabilities we found. Next, we describe the outcomes of the search for learning analytics capabilities. The outcomes are then compared and, finally, combined in the Learning Analytics Capability Model. A dataset with all operationalizations is published online[2].

[2] https://www.researchgate.net/publication/339847879_Learning_Analytics_Capability_Model

4.1 Capabilities for big data analytics and business analytics

Data for this research question was collected in October 2018. Entering our search string in Google Scholar yielded 175 hits. By reading titles and abstracts, it was determined that 150 articles did not meet our inclusion criteria. The remaining 25 articles were combined with the 15 articles already identified by Adrian et al. [31]. Removing duplicates left us with 34 unique articles, which in turn were thoroughly read. Based on the inclusion and exclusion criteria, ten studies were marked as key studies [35]–[44]. In total, the models described in the ten key studies provided 251 different operationalizations. These were coded and based on similarity grouped in 23 different first-order capabilities. The initial coder-agreement was 75%. By categorizing these capabilities based on their characteristics, four second-order capabilities could be distinguished: Data, Management, People, and Technology. We will now elaborate on each of the four second-order capabilities.

Data: The category *Data* contains all capabilities related to the use, quality, reporting as well as sourcing and integration of data – see Table 2. In total, this category contains 71 different operationalizations.

Table 2. Capabilities and operationalization examples for Data (rows 2-100)

Capability	Description	Operationalization examples
Data usage	For what goals are big data analytics and business analytics used	Understand trends, scenario planning, predictive modeling
Quality	What are the characteristics of data quality	No (input) errors in data, standardization, analytics lead to correct and current information
Reporting	How are analytical results presented	Provide actionable insights and proactive recommendations, provide (near) real-time performance metrics
Sourcing and integration	What data sources are integrated and how	Data from multiple systems within and outside the organization, integrate in data warehouse

Management: With 73 different operationalizations, the category Management is the largest of the four second-order capabilities. It involves the benefits of big data analytics and business analytics, governance of analytical processes like capability management, planning and strategy, determining who is responsible and accountable for decisions and their outcomes, benchmarking with external parties, securing funding and investment, as well as the organizational culture and readiness required for the successful deployment of big data analytics and business analytics within an organization – see Table 3.

Table 3. Capabilities and operationalization examples for Management (rows 101-279)

Capability	Description	Operationalization examples
Benefits	What are the benefits of big data analytics and business analytics	Improve the quality of work, lower costs, make work more efficient
Capability management	How are organizational capabilities managed	Incorporate analytics into practices, integrate IT leadership and governance infrastructures, ability to reconfigure and leverage capabilities in order to respond to changes
Culture and readiness	What are cultural aspects and readiness factors for the adoption of analytics	Make decisions on data rather than instinct, trust in data and tools, encouragement to develop data-driven environment
Funding and investment	What kind of funding and investment is necessary and how is it secured	Financial support, given enough time to achieve objectives, consider costs and effects
Market	How to align with the external environment	Compare with competitors, customers, and suppliers
Performance monitoring	How are the performance of analytical processes and outcomes measured	Clear performance criteria, constantly monitor performance
Planning	How to plan the use of analytics in organizational processes	Plan in systematic and formalized ways, enforce adequate plans for analytics introduction, top management create support for analytical initiatives
Responsibility and accountability	How are responsibility and accountability managed	Responsibility and accountability are clear, assign decision rights, provide some authoritative autonomy and financial independence
Strategy	How to align analytics with organizational strategy	Continuously examine the opportunities the strategic use of analytics, identify important business insights and trends, have a clear vision, have top management promote analytics as a strategic priority

People: The third category which can be distinguished from the data is People. This capability comprises the (combined) skills and knowledge stakeholders need to have, ways of communicating and collaborating and with whom, as well as the training stakeholders need to receive in order to successfully do their job – see Table 4. In total, this capability is made up of 58 different operationalizations.

Table 4. Capabilities and operationalization examples for People (rows 280-377)

Capability	Description	Operationalization examples
Collaboration	How is collaboration achieved	Share data and use collaboration portal, coordinate efforts, involve users in planning
Combined skills and knowledge	What combined skills and knowledge do people need to have to perform analytics and act on it accordingly	Hold suitable work experience, possess both technical skills and domain knowledge, create and promote a technical innovation team, ability of senior managers and executives to advocate the use of analytics
Communication	How will information about analytics will be communicated	Listening carefully to the needs, meet frequently to discuss important issues, share information to have access to all available know-how, eliminate identifiable communications bottlenecks
Knowledge	What knowledge do people need to have to perform analytics and act on it accordingly	Business environment, technological trends, critical factors for the success of our organization, exploit existing and explorer new knowledge
Skills	What skills do people need to have to perform analytics and act on it accordingly	Learn new technologies, teaching others, entrepreneurial mindset and vision, network, planning and executing work in a collective environment
Training	What training do people need to receive	Suitable education, training is provided, staff is well trained

Technology: The final category relates to Technology. This capability concerns the way automation is used in big data analytics and business analytics activities, the role of connectivity, the necessary IT-infrastructure, and the required characteristics of big data analytics and business analytics systems – see Table 5. With 49 operationalizations, this capability is the smallest one.

Table 5. Capabilities and operationalization examples for Technology (rows 394-462)

Capability	Description	Operationalization examples
Automation	What is the role of automation in big data analytics and business analytics	Automatic method of maintaining data consistency, automate process for continuously monitoring, automatically notification in case of critical issues
Connectivity	In what way can data sources be connected	Data is shared across organization, open system network mechanisms to boost connectivity, cloud-based data warehouse
Infra-structure	What infrastructure is necessary for analytics	Visualization tools, databases, analytical interfaces, open-source software, self-service analysis applications, enterprise data infrastructure
System characteristics	What are characteristic of (technical) analytical systems	Quick and timely processing, easy to access, adaptable for various analytics tasks, enables work to be shared, protect information

Capabilities for big data analytics and business analytics: When looking at second-order capabilities, it can be noticed that *Technology* is present in all key studies, followed by *Data* which is mentioned in eight of the ten studies. This can hardly come as a surprise, as big data analytics and business analytics are technology-driven and obviously involve the use of data. The management of big data analytics and business analytics and the role of stakeholders are less often present in the existing models. The most frequently mentioned first-order capabilities are *Infrastructure* and *Sourcing & Integration*, which both can be found in eight key studies. Almost all first-order capabilities are present in two or more studies. The only exception is *Training,* which is mentioned in only one study. Moreover, there are just two studies [40], [43] in which all second-order capabilities are present.

4.2 Capabilities for learning analytics

Data for this research question was collected in March 2019. Entering our search string in the ERIC and ACM databases yielded 102 hits. By reading titles and abstracts, it was determined that 90 articles did not meet our inclusion criteria. The remaining 12 articles were combined with the 12 articles already identified by Colvin et al. (2017). Removing duplicates left us with 17 unique articles, which in turn were thoroughly read. Based on the inclusion and exclusion criteria, five studies were marked as key studies – see Table 6. As the research of Colvin et al. [9] is essentially two studies in one – each with their unique objective – we split their research accordingly. This provides us with a total of six key studies that are included in the next phase of our research. From the key studies, 210 operationalizations were extracted and coded according to the *a priori* coding scheme. Initial coder-agreement was 82%, where almost all discrepancies had to do with the classification of first-order capabilities. Disagreements between the two coders were resolved by discussion.

Table 6. Key studies from the learning analytics domain

Reference	Third-order capability	Study objective(s)
Norris & Baer [45]	Organizational capacity for student success	Describe the state of the industry and the current and future nature of the analytics gap in higher education.
Colvin et al. [9] (study 1)	Learning analytics readiness factors	Understand how senior institutional leaders perceived learning analytics including the drivers, affordances, and constraints that shape LA within their institutional context
Colvin et al. [9] (study 2)	Dimensions for sustainable uptake of learning analytics	Investigating the factors perceived as necessary for establishing sustainable LA implementations that demonstrate long term impact.
Ferguson et al. [6]	ROMA elements	Offer tools and case studies that will support educational institutions in deploying LA at scale to achieve specified learning and teaching objectives.
Bichsel [46]	Analytics maturity factors	Set out to assess the current state of analytics in higher education, outline the challenges and barriers to analytics, and provide a basis for benchmarking progress in analytics.
Tsai et al. [7]	SHEILA elements	Presents a framework that can be used to assist with strategic planning and policy processes for learning analytics.

Many of the capabilities could be coded according to the *a priori* coding scheme. However, 16 operationalizations do not fit well within this coding scheme. These operationalizations concern privacy aspects and the ethical use of learning analytics. Therefore, we construct a fifth second-order capability: *Privacy & Ethics*. Although it is not mentioned in all studies, this category is present in existing learning analytics models. This is hardly a surprise, as privacy and ethics are often discussed in learning analytics literature [47].

Privacy & Ethics: The category Privacy & Ethics comprises five different capabilities – see Table 7. They involve the ethical use of learning analytics, the role of human decision-making, the compliance with legal regulations and in particular privacy laws like GDPR, the security of data and information, and transparency about learning analytics.

Table 7. Capabilities and operationalization examples for Privacy & Ethics (rows 378-393)

Capability	Description	Operationalization examples
Ethics	How to perform analytics in an ethical way	Policy on ethical use, anticipate ethical dilemmas, establish an ethics committee
Human decision-making	What is the role of humans in analytical decision-making	Account for human dimensions, outcomes must be actionable, make no decisions without human evaluation
Legal compliance	How to comply with the law	Data ownership, legal frameworks, third party access
Security	How to secure data and information	Have information security policies, specify rights and privileges, guarantee data security
Transparency	In what way to create transparency about analytics	Be transparent about data use and algorithms, make research reproducible, be clear how 'success' is conceived

Capabilities for learning analytics: Next to an additional second-order capability, the analysis of learning analytics literature also provided some first-order capabilities unique for the learning analytics field – see Table 8.

Table 8. Capabilities solely present in learning analytics literature

Category	Capability	Description	Operationalization examples
Data	Feedback on analytics	Allows users to provide feedback on the analytics	Provide opportunities to feedback on results, seek feedback, be judged useful by learners
Management	Evidence-based and theory-driven	Include evidence and theory in the design of analytics	Blend with proven best practice, be driven by pedagogy, engage with existing literature
Management	Implementation and deployment	What factors to consider when implementing and deploying analytics	Integrate in processes, implement top-down, decide on forms of interventions
Management	Policies and code of practices	How to (re)-formulate policies	Change written policy, review original policy objectives and vision, consult relevant policies and codes of practice
People	Stakeholder engagement	Who to involve in analytics	Engage all stakeholders, involve students, invite teaching staff to contribute
People	Stakeholder identification	Who to identify	Identify primary users, senior management, academic teams, internal advocates

4.3 Differences and similarities

To identify differences between big data analytics and business analytics capabilities on one hand and learning analytics capabilities on the other, we start with an analysis of the operationalization instances per category. That is, the total number of operationalizations per category. On average, learning analytics key studies provide more operationalizations than studies on big data analytics and business analytics. One of the main reasons for this is the work of Colvin et al. [9], which on its own is responsible for 87 operationalizations. As shown in Table 9, operationalizations for the categories *Data* and *Technology* belong to a large extent to the big data analytics and business analytics literature. Operationalization of the category *Privacy & Ethics*, on the other hand, can only be found in learning analytics studies. It is remarkable that this category is absent in the big data analytics and business analytics models, even those focusing on healthcare and thus patient data (e.g. [43]). The remaining two categories – *People* and *Management* – are more equally distributed across the literature. However, differences exist also within each category. We now move on to a more in-depth analysis per category.

Table 9. Operationalization instances for big data analytics, business analytics, and learning analytics capabilities

Capability category	BDA/BA (n=10)	LA (n=6)
Data	71	28
Management	73	106
People	58	40
Privacy and ethics	0	16
Technology	49	20
Total	**251**	**210**

Looking at the category *Data*, one capability is only present in learning analytics literature: *Feedback on analytics.* This capability allows end-users to provide feedback on the (visualization of) analytics they receive. Based on this feedback, analytical outcomes can be improved and better support the beneficial application of insights gained from the analytics. *Sourcing & Integration*, on the other hand, is almost absent from learning analytics models. Nonetheless, it is an important capability as learning analytics ideally uses data from multiple sources [48] and integration between those sources is paramount for timely and error-free analytics.

With regards to the second-order capability *Management*, it appears that learning analytics models are more internally-oriented than big data analytics and business analytics models, as the latter also considers the external environment (*Market*) they operate in. Learning analytics models, on the other hand, consider evidence and theory, for example, about pedagogy, as important factors for analytical endeavors. Moreover, the learning analytics models mention implementation and deployment as separate capabilities to build to make sure learning analytics integrates with existing processes and considers the appropriate forms of intervention in advance. This is often described in policies and codes of practice, which justifies and elaborates on the use of analytics in educational settings.

In the category *People*, the training of people involved in analytics and the knowledge required for analytics is less often mentioned in learning analytics models than in big data analytics and business analytics models. This is in line with the findings of Tsai & Gašević [17]. However, the identification and engagement of stakeholders is solely mentioned in learning analytics literature.

Looking at *Technology*, the use of automation is only present in big data analytics and business analytics models. Also, connectivity between systems in the organization is hardly mentioned in learning analytics models. This is in line with the previous observation that the sourcing and integration of data sources is underrepresented in learning analytics models. Both academia and practitioners should be aware of these capabilities and consider them when working on learning analytics adoption.

4.4 The learning analytics capability model

By researching big data analytics, business analytics as well as learning analytics literature, we found five categories with 34 different capabilities comprising 461 operationalizations. Combining all these capabilities leads to the first version of the Learning Analytics Capability Model: a model specifying what organizational capabilities higher educational institutions need to develop to support the successful adoption of learning analytics and in what way to operationalize them. The model facilitates an increase of learning analytics adoption by higher educational institutions and, as a consequence, helps the field of learning analytics advancing to a higher degree of maturity. We present the Learning Analytics Capability Model in Fig 3.

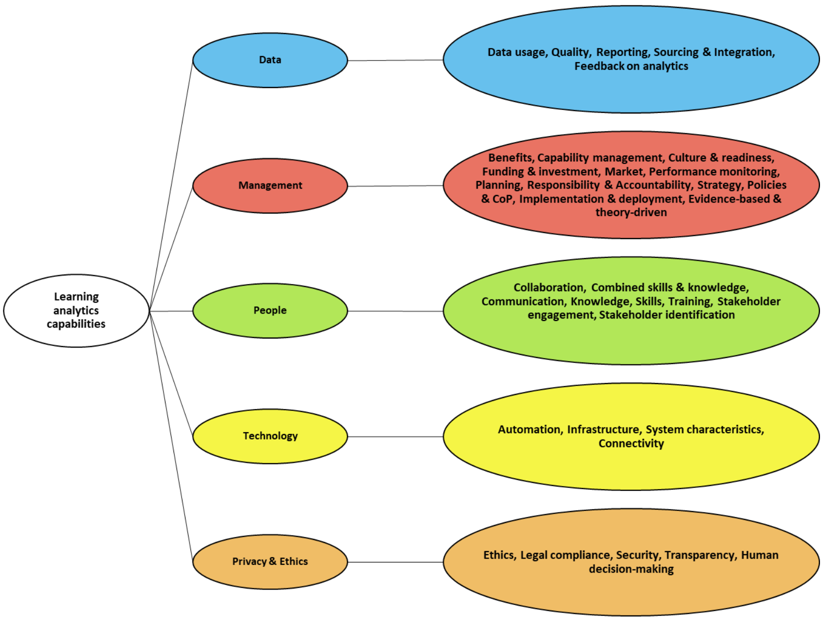

Fig. 3. Learning Analytics Capability Model

5 Conclusion and Discussion

This literature review provides an answer to the question of what organizational capabilities higher educational institutions need to build for the successful adoption of learning analytics. Because learning analytics is a relatively young research field, we included relevant literature from adjacent research fields, i.e., big data analytics and business analytics. These fields are more mature when it comes to the usage of data to enhance processes and their outcomes. Other research towards learning analytics adoption focusses on certain aspects like policy (e.g., [6], [7]) or privacy (e.g., [3], [4], [14]) but by combining capabilities found in multiple key studies, we now present a model which includes all these aspects: the Learning Analytics Capability Model. Moreover, not only does the model describe the necessary capabilities, it also provides ways to operationalize these capabilities. We thereby enable practitioners, such as senior managers and policymakers, to make strategic and actionable plans towards the adoption of learning analytics in their institution.

The Learning Analytics Capability Model contains five categories: Data, Management, People, Technology, and Privacy & Ethics. These categories comprise 34 different capabilities, for which we provide 461 operationalizations. Some capabilities could only be found in learning analytics literature, for example allowing users to provide feedback on the analysis they receive. However, some other capabilities are presently absent from the learning analytics frameworks we analyzed: i.e., sourcing of data and integration of data sources, the training of stakeholders and learning analytics users in particular, the automation of methods and processes, and connectivity between different systems. We argue that these capabilities must become more prominently present in learning analytics research and practice. When it comes to privacy and ethics, the learning analytics field seems to be quite mature. Although other researchers found that much learning analytics literature does not mention ethical aspects [12], the studies we researched did clearly pay attention to this important aspect. Surprisingly, it is absent in the key studies on big data analytics and business analytics. We recommend researchers and practitioners from these fields to be more aware of privacy and ethics capabilities in the development of big data or business analytics within organizations, and we provide the concrete operationalization of such capabilities extracted from learning analytics literature.

We recognize that our study has limitations. First and foremost, it only relies on secondary data. That is, we conducted a literature review and used existing frameworks to construct our model, so it is not empirically evaluated and validated. Therefore, we consider the current Learning Analytics Capability Model to be the first version and plan to enhance it via a mixed-method approach, i.e., conduct additional case studies to add empirical data to the model and make it more rigorous. Also, the model is yet mainly descriptive and not easily applicable by practitioners who wish to use it. As implementation of learning analytics within an institution is not easy and straightforward, we will enhance the usability of our model for users so it becomes more prescriptive and makes clear how to apply the model to practical settings. A final limitation is the absence of contextual differentiation. All learning analytics-oriented key studies focus on Anglo-Saxon countries, with the Europe-focused SHEILA framework [7] being the only exception. This is in line with the observation of Nouri et al. [16] that at a national or European level, countries yet pay little attention to learning analytics policies and guidelines. As educational ecosystems and thus institutions differ between parts of the world, countries, and even locally, the required capabilities for learning analytics may be different as well. We suggest further research to adapt the Learning Analytics Capability Model for use in specific educational ecosystems to account for differences between, for example, countries.

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