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Refining the Learning Analytics Capability Model: A Single Case Study

Justian H. Knobbout
HU University of Applied Sciences Utrecht, justian.knobbout@hu.nl

Esther van der Stappen
HU University of Applied Sciences Utrecht, esther.vanderstappen@hu.nl

Johan Versendaal
HU University of Applied Science Utrecht, johan.versendaal@hu.nl

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Completed Research

Justian Knobbout
HU University of Applied Sciences Utrecht
justian.knobbout@hu.nl

Esther van der Stappen
HU University of Applied Sciences Utrecht
esther.vanderstappen@hu.nl

Johan Versendaal
HU University of Applied Sciences Utrecht
johan.versendaal@hu.nl

Abstract

Learning analytics can help higher educational institutions improve learning. Its adoption, however, is a complex undertaking. The Learning Analytics Capability Model describes what 34 organizational capabilities must be developed to support the successful adoption of learning analytics. This paper described the first iteration to evaluate and refine the current, theoretical model. During a case study, we conducted four semi-structured interviews and collected (internal) documentation at a Dutch university that is mature in the use of student data to improve learning. Based on the empirical data, we merged seven capabilities, renamed three capabilities, and improved the definitions of all others. Six capabilities absent in extant learning analytics models are present at the case organization, implying that they are important to learning analytics adoption. As a result, the new, refined Learning Analytics Capability Model comprises 31 capabilities. Finally, some challenges were identified, showing that even mature organizations still have issues to overcome.

Keywords

Learning analytics, capabilities, resource-based view, case study.

Introduction

In the past decade, the higher educational domain witnessed the emergence of a new research field: learning analytics. Learning analytics is the analysis and visualization of learner data with the goal to improve learning and the learning environment (LAK 2011). One of its main drivers is IS/IT, as the digitalization of education led to the increased availability of learner data (Ferguson 2012). However, despite the promising results, the uptake of learning analytics by higher educational institutions remains low (Gasevic et al. 2019). One of the main causes for this is the complexity of implementation, which requires attention to many different dimensions. Several learning analytics adoption models are designed, for example, ROMA (Ferguson et al. 2014), SHEILA (Tsai et al. 2018) and LALA (Pérez-Sanagustín et al. 2019). However, these existing models often focus only on specific elements like policy or privacy and ethics, or lack descriptions on how to operationalize important dimensions. These shortcomings limit the practicality of the models and help higher educational institutions only to a certain degree. To overcome the shortcomings and support higher educational institutions in their quest to adopt learning analytics successfully, the Learning Analytics Capability Model is designed (Knobbout and van der Stappen 2020). As higher educational institutions need to make strategic decisions about resources and institutional capacities (Arnold et al., 2014), the model takes a resource-based perspective. The resource-based view attributes organizational performance to its resources and is used to study the uptake of business analytics and big data analytics - two research fields adjacent to learning analytics. The Learning Analytics Capability Model describes what organizational capabilities higher educational institutions need to build to support the uptake of learning analytics. Moreover, the model provides clear operationalizations of these capabilities, helping institutions' senior management and policymakers to implement learning analytics successfully. It is the result of a literature review towards capabilities for business analytics, big data analytics, and learning analytics. It comprises 34 different capabilities divided over five second-order categories.

Momentarily, the Learning Analytics Capability Model is only grounded in theory. Drawing from Design Science Research, the evaluation and refinement of a made artifact (the model) is an important part of the design process (Hevner 2007). Therefore, before the Learning Analytics Capability Model can be used in practice, it needs thorough evaluation and refinement. To perform the first refinement of the model, we conduct a single case study. This way, we include empirical data and practical experience to the model. This paper provides an answer to the research question "*How can the Learning Analytics Capability Model be evaluated and refined based on empirical data from a single Dutch higher educational institution that is mature in the use of learner data to improve learning?*" The case study is conducted at a higher educational institution that is mature in the use of data to improve education and comprised four interviews with different stakeholders. Transcriptions of the interviews are coded and compared with the theoretical Learning Analytics Capability Model. In turn, the model is improved as the interviews provide new insights into the capabilities necessary for successful learning analytics implementation.

The remainder of this paper is structured as follows. First, we describe relevant work related to the resource-based view and capabilities for big data analytics, business analytics and learning analytics, as well as the Learning Analytics Capability Model. Next, we elaborate on the research method, including case selection and interview procedures. We then comparison of the theoretical Learning Analytics Capability Model with the collected, empirical data, and describe the refinements we make to the model. Next, we draw conclusions from the results and answer the research question. Finally, we discuss our work and provide directions for future research.

Theoretical Background

The resource-based view attributes organizational performance to its resources and, in order to obtain sustained competitive advantages, these must be valuable, rare, inimitable, and non-substitutable (Barney 1991; Bharadwaj 2000). Different kinds of resources can be distinguished: financial resources, physical resources, human resources, technological resources, organizational resources, and reputation (Barney 1991; Grant 1991). Moreover, resources can be subdivided into two distinct groups: assets and capabilities (Helfat and Peteraf 2003; Wade and Hulland 2004). Assets involve anything which can be deployed by an organization to create, produce and offer its goods or services to a market and can be either be tangible, intangible or personnel-based (Bharadwaj 2000). In contrast, capabilities are repeatable patterns of actions in the use of these assets (Wade and Hulland 2004) and involve "complex patterns of coordination between people and between people and other resources" (Grant 1991, p. 122). Capabilities refer to an organization's capacity to deploy other resources and ownership cannot be transferred between organizations as they are deeply embedded in the organization (Makadok 2001). As a result, capabilities are no commodities that can be bought, but they need to be built to effectively interact with the organizational processes and procedures.

The resource-based view is utilized to study the capabilities needed for big data analytics (Gupta and George 2016). Big data analytics provides the required knowledge about the handling, analysis, and visualization technologies of large and complex datasets (Chen et al. 2012). Based on the analysis of 15 key studies on big data analytics, Adrian, Abdullah, Atan and Jusoh (2018) show that possessing the right capabilities is an important factor for organizations that adopt big data analytics. These capabilities relate to, among others, management, technology, talent, and information processing. The resource-based view is also applied to study capabilities for business analytics (Cosic et al. 2015). Business analytics uses the analysis of data to understand and manage businesses more effectively (Kohavi et al. 2002). Business analytics and big data analytics are comparable to analytics in educational settings (Barneveld et al. 2012; Picciano 2014). Like its non-educational counterparts, learning analytics can bring competitive advantages to the educational domain when institutions invest in resources and institutional capacities (Arnold et al. 2014).

Learning analytics is "the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environment in which it occurs" (LAK 2011). The learning analytics process involves multiple steps: the generation and collection of learner data, the analysis and visualization of these data, and interventions (Clow 2012). Learning analytics could affect and improve learning processes, learning environments, student performance, and departmental performance (Knobbout and van der Stappen 2018). Many higher educational institutions are interested in learning analytics, but not many have already adopted it to address institutional and educational challenges (Gasevic et al. 2019). Issues related to implementation may be technical but also involve strategic planning and policy (Tsai and Gašević 2017). Empirical research by Ifenthaler and Yau (2019) 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. However, despite the importance of having the right resources and capabilities, the resource-based view is only recently used to study capabilities for learning analytics (Knobbout and van der Stappen 2020). Based on existing literature on business analytics, big data analytics and learning analytics, the authors designed the first, theoretical version of the Learning Analytics Capability Model. Via the open coding of 461 operationalizations found in 15 key studies, 34 different capabilities were identified. These capabilities could then be categorized into five second-order capabilities: *Data, Management, People, Technology,* and *Privacy & Ethics*. Six capabilities were only present in literature on business analytics and big data analytics: *Sourcing & Integration, Market, Knowledge, Training, Automation,* and *Connectivity*. Since these research fields interconnect with learning analytics, these capabilities were adopted to the Learning Analytics Capability Model – a process called exaptation (Gregor and Hevner 2013).

To enhance its rigor, the Learning Analytics Capability Model must be evaluated and refined (Hevner 2007; Hevner et al. 2004). Evaluation is about identifying weaknesses in the designed artifact. In our situation, we must research whether any capabilities are missing in our model, whether the exapted capabilities are indeed present at the case organization, and whether the capability definitions are explicitly enough to capture the ways capabilities are operationalized. Based on the outcomes of this identification, the model will be refined. To perform the task of evaluation and refinement, we conduct a case study at a higher educational institution that is experienced in the use of learner data to enhance learning. The research methodology for this study is described in the next section.

Research Method: Protocol Definition and Execution

In our study, we opt for a case study to verify and complement what has been found from literature. Using the case study, we study contemporary events without the need to control behavioral events (Yin 2013). A case study is a suitable evaluation method to study a designed artifact in an organizational environment (Hevner et al. 2004). For preparation, we take notice of the case study protocol guidelines from Maimbo and Pervan (2005).

Preamble

For the case study, we take interviews and consult documentation. We ask the interviewees to agree on the proposed anonymous scientific publication of the results of the case study. We explain the reason for the research to the interviewees and ask them to sign a confidentiality agreement. After transcribing the interviews, the audio files are deleted. Data is stored in compliance with the GDPR.

Procedure

Especially in Europe, institutions that successfully apply learning analytics are scarce (Gasevic et al. 2019), thus providing an unusual case. This justifies the use of a single case study that focusses on a single unit of analysis (Yin 2013). The unit of analysis in our study is the analytics team and its internal customers of a Dutch university that uses learning analytics across the organization. We select the case by consulting a group of learning analytics experts in the Netherlands. They suggest a particular case organization - which we anonymize to The Netherlands University (TNU) - as it was the first higher educational institution in the Netherlands publishing a code of practice related to the analysis of student data and because it already has a couple of years' experience with organizational-broad use of learning analytics. TNU is a large academic university with around 25,000 enrolled students and located in the Netherlands. To ensure the organization's learning analytics maturity, we additionally apply the EDUCAUSE maturity model (Bichsel 2012). This model is partly based on the work of Davenport and Harris (2007) but adjusted to the educational domain and can be used to score various dimensions important to learning analytics uptake. TNU scores well on each dimension of the EDUCAUSE model, that is, four on a five-point scale. Such a score is comparable to stage 4 (analytical company) of the Davenport and Harris model, so the organization is suitable for the study at hand. The interviews took place at TNU in December 2018 and January 2019, and the interview duration was between 40 and 90 minutes.

Learning analytics is a multidisciplinary field including "educators, learning scientists, computer scientists, administrators, and policymakers" (Suthers and Verbert 2013), and consequently, the interviews need to reflect this. To ensure a broad view of the topic, we select interviewees with different roles within the learning analytics process at TNU, including users of learning analytics within the organization. The first person to interview is the manager of the analytics team, with whom contact was already established. From there on, we apply a snowballing technique to select the next interviewees. To further enhance the quality of our study, we also request relevant (internal) documentation to support statements made during the interviews. This form of data triangulation increases the quality of the study (Yin 2013). In total, four interviews are conducted. We send leading questions from the interview protocol (in Dutch) in advance so the interviewees can prepare their answers and bring relevant material to the interview. Interview questions are derived from the theoretical Learning Analytics Capability Model (Knobbout and van der Stappen 2020)[1]. The characteristics of each interviewee and on what category of the theoretical model the interview questions were focused, are described in Table 1.

	Job title	**Relation to learning analytics**	**Question categories**
Interviewee A	Data engineer	Member of the analytics team	Data, Technology, Privacy & Ethics
Interviewee B	Project leader	Manager of the analytics team	Data, Management, People, Technology, Privacy & Ethics
Interviewee C	Student advisor	User	Data, Management, People, Privacy & Ethics
Interviewee D	Policymaker	User	Data, Management, People, Privacy & Ethics

Table 1. Interviewee Characteristics

Research Instrument

We use open semi-structured face-to-face interviews to collect data. We create an interview protocol with procedures and questions and discuss this with a panel of researchers. We anticipate fine-tuning this protocol after each interview. Interviewees are requested to bring relevant archival data – documents, presentations etc. - to the interviews. Also, publicly available archival data (the code of practice, presentations) from TNU are collected. The use of these data is twofold: 1) to help guide the interviews and allow for ad-hoc questions about the documentation brought by the interviewees, and 2) to later clarify and verify statements made by the interviewees.

Data Analysis Guidelines

We record the interviews and transcribe each interview verbally. In line with suggestions by Runeson and Höst (2009), the main researcher performs the transcription, while multiple researchers do the subsequent coding of the transcriptions. Due to technical malfunctions, only half of the interview with interviewee D was recorded. Luckily, notes were taken during the interview, and these notes were used to reconstruct the interview. We send transcriptions to the interviewees so they can check for errors or misinterpretations. No objections or requests for change were received. Next, we will code the transcriptions in Atlas.ti. We apply the principle of axial coding, where the codes are structured based on existing knowledge (Strauss and Corbin 1990). A-priori coding comes from our initial Learning Analytics Capability Model (Knobbout and van der Stappen 2020). We place interview fragments not matching the existing codes in a separate category for later analysis. Archival data is used to clarify and validate comments made by the interviewees. Two researchers work in parallel and code the same interview. The results are then to be discussed, after which the coding protocol with code definitions can be adjusted. This process is to be repeated until all interviews are coded. After the coding process is finished, we discuss the results with a third researcher. The interviews

[1] Interview questions (in Dutch) are available on request by contacting the first author.

are in Dutch so all quotes in this paper are our translations. In the next section, we present the results of our analysis.

Findings

The analysis of the transcriptions of four different interviews at the case organization resulted in 424 assigned codes. Next to the five categories of capabilities, a list of challenges emerged from the data – see Table 2. The interviews of interviewees A and B contained significant more codes than the interviews of interviewees C and D. This is not surprising, as A and B work at the back end of the analytics process while C and D are primarily users and only see the outcomes. Codes related to the category *Data* appear the most, followed by *People*. Codes about *Privacy & Ethics* appeared the fewest, and this is the only category that is not mentioned in all interviews. Collected documentation included the organization's policy on learning analytics, a list with (learning) data sources and presentations about the subject given by members of the analytics team. The most important conclusion is that all capabilities necessary for learning analytics adoption are present in the current Learning Analytics Capability Model. Nonetheless, several improvements could be made to the model.

	Interviewee				
Category	**A**	**B**	**C**	**D**	**Total**
Challenge	18	9	7	9	43
Data	49	37	18	14	118
Management	31	48	8	11	98
People	27	46	12	16	101
Privacy & Ethics	3	12	0	3	18
Technology	30	11	4	1	46
Total	**158**	**163**	**49**	**54**	**424**

Table 2. Codes Assigned to Each Interview

Comparison with the Theoretical Learning Analytics Capability Model

When we compare the theoretical model with the collected data, not all capabilities from theory appear in practice at TNU. The capabilities *Performance Monitoring* and *Human Decision-Making* were not mentioned in any of the interviews. *Performance Monitoring* relates to the monitoring of the learning analytics process performance, i.e., does the analytics improve learning according to pre-defined criteria. One reason for the interviewees not mentioning this aspect could be because the actual interventions are performed by other stakeholders who do not relay the improvements back to the analytics team. However, to enhance the analytical process, it would be good for TNU to keep track of the improvements made on education. The absence of *Human Decision-Making* in the interviews might be explained by the fact that in the Netherlands, fully automated decision-making based on student data is prohibited by law (Engelfriet et al. 2017) so humans are by default involved in the decision-making process.

In a previous study (Knobbout and van der Stappen 2020), we learned that several capabilities, e.g., *Sourcing & Integration* and *Automation*, were present in the literature on business analytics and big data analytics but absent from existing learning analytics models. Based on the principle of exaptation (Gregor and Hevner 2013), they were included in the Learning Analytics Capability Model but their relevance to the learning analytics domain remained unclear. During the interviews, however, these absent capabilities were mentioned by the interviewees and thus appear to be necessary for the successful uptake of learning analytics within an institution. For example, documentation shows 52 different data sources, so *Sourcing & Integration* is an important capability for TNU. Data could be extracted from the Management Information System, the Virtual Learning Environment, the Enterprise Resource system, and many more. Interviewee A comments on the integration of different sources: "*it is easy to do because we use linking tables, so it all translates to each other*". The capability *Automation* plays a role there as well: "*We have* *automated as much as possible so the [analytics] team members are not wasting time linking things together*" (Interviewee B). Also, by automating processes, the quality of data is secured: "*After each step, automated tests are conducted [...] so we can check each step"* (Interviewee B).

The capability *Training* is clearly present at TNU: "*Once, we had a statistics course with the whole team for a full week*" (Interviewee A) and "*with each other, we procure education. [The team members] decide what skills we need to develop*" (Interviewee B). Not only the analytical team receives training, but users do as well: *"they got a short training – one afternoon – on how to interpret [the analytical outcomes]*" (Interviewee B). This links to the capability *Knowledge,* as both the team members and the users often need extra training to attain relevant knowledge: "*At the moment, we don't have much knowledge about text mining" (Interviewee A), and "you really need to know what you're looking at*" (Interviewee C). Especially users should have the right knowledge about how to interpret the analytical outcomes, as they are the ones performing interventions.

Higher educational institutions do not operate in a vacuum. That is, some comments were made with regards to the capability *Market*: "*another university is interested in procuring [our method] from us*" (Interviewee B) and "*They used material from England, from [JISC]. Well, we used the things we thought to be important*" (Interviewee B). An adjacent capability is *Connectivity*, which describes the external connection between systems: "*We use SAP, but other institutions use other systems so transferring data is difficult*" (Interviewee D).

The presence of the capabilities unique for business analytics and big data analytics at TNU confirms their adoption to the learning analytics domain and thus their inclusion in the Learning Analytics Capability Model.

Refinements to the Theoretical Learning Analytics Capability Model

An important outcome of our study is that no capabilities seem to be missing to the Learning Analytics Capability Model. Nonetheless, several refinements [2] could be made based on the collected data. Refinements concern the merging of capabilities, the renaming of capabilities, and/or the reformulation of the capability definitions. Most changes affect the categories *Data, Management,* and *People*. In practice, some capabilities overlap to such a degree that merging them would improve the model. Also, refinement was deemed necessary when the capability definitions from the theoretical model did not reflect the statements made by the interviewees. Often, the name or the definitions needed clarification to describe better what exactly is covered by each capability. Refinements were established through multiple rounds of discussion between three researchers (two of whom coded the data). During our analysis, some challenges were identified. These could often be linked to certain capabilities, but they do not have a solution yet. We present some of the found challenges to guide future research. We will now discuss the most important changes per type of refinement.

Merging Capabilities

In theory, the difference between knowledge and skills is easily described. In practice, however, it is hard to distinguish between skills without considering the need for related knowledge and vice versa. For example, Interviewee B describes a skill needed by members of the analytics team: "*programming in R*". Although this quote only implies the need for a certain skill, without knowledge about both programming and R, this skill is impossible to master. This is often the case. Therefore, we merge capabilities *Knowledge* and *Skills* in the already existing capability *Combined Skills & Knowledge*.

The same principle applies to the capabilities *Stakeholder Identification* and *Stakeholder Engagement*. Without the ability to identify the right stakeholders, they cannot be engaged. Interviewee C comments: "*Academic advisors are of course involved*". These advisors need to be identified before they can be involved in the analytical process. As a result, we merge the *Stakeholder Identification* and *Stakeholder Engagement* into the new capability *Stakeholder Identification* & *Engagement*.

[2] See https://hbo-kennisbank.nl/details/sharekit_hu:oai:surfsharekit.nl:88cdbc33-c3d0-4748-b81d-263f6ad44876?q=LACM for an overview of the original and the refined capabilities, including their definitions.

The capability *Planning* describes the planning of the learning analytics implementation. However, the Learning Analytics Capability Model also comprises a separate capability *Implementation & Deployment* that describes the actual implementation. Although *Planning* relates to the process before and *Implementation & Deployment* to the process during implementation, these two capabilities overlap. Moreover, after implementing learning analytics into the organization, the work is not finished. Learning analytics processes need to be refined, optimized, and planned. As stated by Interviewee B: "*We have a long list of things we want next – new datasets, improving quality of tests, doing things we believe are interesting for TNU.*" Hence, we both combine and rename these two capabilities to *Implementation Deployment & Application*.

Renaming Capabilities

The capability *Market* is renamed to *External Environment*, as not all external collaboration is commercial as the term 'Market' suggests. As mentioned earlier in this paper, this capability describes all influences from outside the organization. This includes the use of material and tools from external parties, the hiring of external personnel, requests and demands from external (governmental) bodies, and sharing materials, knowledge and experiences with other (higher) educational institutions.

Benefits describes the benefits of learning analytics for the organization, which is not a capability per se. It is important though to identify the benefits to education as this should be part of the learning analytics design (Wise 2014). Higher educational institutions, therefore, should be able to describe the benefits they want to achieve with learning analytics. In the Learning Analytics Capability Model, we rename the capability *Benefits* to *Identifying Benefits*.

Capability Management is needed to manage existing capabilities. Also, it should include the development and reconfiguration of these existing capabilities. This principle aligns with the concept of *dynamic capabilities*: "routines by which firms achieve new resource configuration" (Eisenhardt and Martin 2000). To better reflect the ongoing change of capabilities already present at the organization, we rename this capability to *Capability Development*. Moreover, we use this capability to describe challenges for which the solutions are already known, i.e., the organization knows how to deal with problems.

Improving Capability Definitions

Besides many small changes to the capability definitions, four major improvements were made. First, *Data Usage* relates to the goals of analytical processes. However, during the interviews, multiple comments about intervention strategies were made, for example, improved communication towards students (Interviewee B, Interviewee D), or supporting students with data-informed planning tools (Interviewee B). The attention for interventions is not surprising, as it is part of the learning analytics process (Clow 2012). Also, at TNU data is often aggregated: "*We aggregate to a level on which we can do analyses*" (Interviewee A). Aggregating data is a form of summarizing and thus use of data. So, *Data Usage* is broader than only the goals of analytics, and we change its definition to "in what way data analysis is used to improve education. It contains data aggregation, different kinds of analysis, the goals of the analysis, and the interventions performed based on the outcomes of the analysis."

Next, three capabilities need better definitions as they partly overlap and caused confusion while coding the interview data: *Reporting, Communication,* and *Collaboration*. *Reporting* describes in what way the outcomes of data analysis are presented to the various stakeholders (dashboards, reports, etc.) and what the requirements of the presentation are. In contrast to *Communication*, the flow of information is one-way, i.e., from the party delivering the analytical outcomes to the party receiving them. That said, *Communication* relates to the flow of information between (groups of) stakeholders. This includes communication between users and the party delivering the learning analytics about the needs and possibilities ('demand and supply'), the communication mechanisms and the types of information that are shared between different (groups of) stakeholders. Finally, *Collaboration* describes the active cooperation between parties - either within a group of stakeholders or between groups of different stakeholders, and either internal or external. This capability also includes the mechanisms via which collaboration is achieved.

Challenges Mentioned by Interviewees

The case study provided insight into the capabilities present at TNU but also in some of the challenges faced by the organization when maturing in the use of learner data. These challenges often relate to existing capabilities, like *Sourcing & Integration*: "*sometimes we need to couple [data sets] ourselves because others did not couple or aggregated it in the right way*" (Interviewee A), or *Training*: "*Instructional video's or manuals could help, but they are outdated pretty fast because the developments go very quick*" (Interviewee D). Solutions are not always clearly present, making it hard to mature in the use of learning analytics. We take the challenges into consideration and use them as directions for future research.

Conclusion

The aim of this study is to provide an answer to the question "*How can the Learning Analytics Capability Model be evaluated and refined based on empirical data from a single Dutch higher educational institution that is mature in the use of learner data to improve learning*?" By conducting a single case study, we collected empirical data on capabilities important to the successful uptake of learning analytics. We take a resource-based perspective, and because capabilities cannot be transferred between organizations, we emphasize the importance of higher educational institutions to develop their own capabilities. As Interviewee D correctly mentions: "*even when we sell our model or [the manager of the analytics team], another organization cannot do what we do*". Based on the analysis of the collected data, seven capabilities from the previous Learning Analytics Capability Model are merged, three of them are renamed, and all definitions are improved. Eventually, we made significant improvements to the model. The new, refined Learning Analytics Capability Model comprises 31 capabilities – see Figure 1.

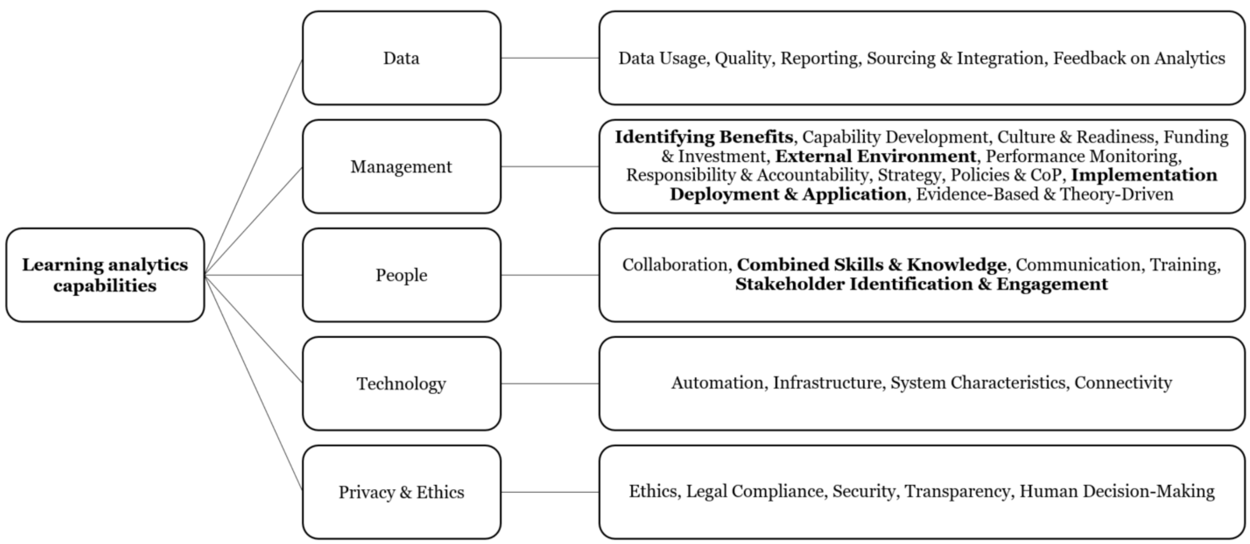

Figure 1. Refined Learning Analytics Capability Model (Changed Capabilities in Bold)

Our study has both scientific and practical relevance. First, the Learning Analytics Capability Model provides a relevant and rigorous set of clearly defined learning analytics capabilities. Second, to our knowledge, the Learning Analytics Capability Model is the first model using the resource-based view in relation to learning analytics. This helps academics to extend their vision on learning analytics adoption as it eases the comparison between analytical capabilities of higher educational institutions and those of organizations outside the educational domain. Third, the Learning Analytics Capability Model identified some important capabilities missing from extant learning analytics models, helping researchers to improve these models. Finally, the model helps practitioners to develop the right capabilities so higher educational institutions can adopt learning analytics more efficiently.

Discussion & Future Work

We are aware that our work has some limitations. First, we only interviewed four stakeholders at a single organization. Although care was taken that the interviewees have different roles, experiences, and insights, it is possible that more interviews would have brought up new information important to our study. The same applies to the selection of a single organization – other organizations might have different capabilities yet unknown to us and therefore absent from our model. This study, however, is the first evaluation of the Learning Analytics Capability Model and a multiple-case study with a broad selection of different organizations is planned in the coming year. The refined model is currently used as blueprint to develop a digital tool that allows institutions to measure what learning analytics capabilities they already possess and what others they still need to build. Data collected via this tool will be used to further refine our model. This follows the call of Hevner (2007) for multiple iterations of the design cycle. Second, in addition to interviews, archival data were used for clarification and verification purposes. These data, however, were not coded themselves. Therefore, relevant information in the collected documentation might be missed. We suggest the coding of these data and comparison with the results from the study at hand as a future research activity. During the analysis, we discovered of some challenges currently faced by the case organization. Solutions to these challenges are not always easy. They might be widespread ("[the lack of] s*tatistical knowledge is often a problem*", Interviewee D), hard to solve ('*in most BI-systems, field names are restricted*", Interviewee A), or take considerable time and effort ("*you need to get the managing directors on board*", Interviewee B). In our future research, we will focus on these challenges, helping higher educational institutions - and the educational domain in general - to mature in the adoption and use of learning analytics.

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