Small Business, Big Data

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Small Business, Big Data: An assessment framework for (big) data analytics capabilities in SMEs

Naomi Moonen, Jeroen Baijens, Mahdi Ebrahim and Remko Helms

ABSTRACT

Though firms are investing a lot in big data analytics (BDA), it is not well-understood how this creates business value. Prior research identified important dimensions of BDA capabilities (BDACs) of large organizations, but these capabilities are also relevant for small and medium-sized enterprises (SMEs) in order to sustain and improve their competitiveness. However, due to major differences between large and small organizations, BDAC dimensions are not directly transferrable to SMEs. Therefore, this research aims to develop a framework to assess BDACs of SMEs. A preliminary assessment framework is developed from a systematic literature review that in a later stage is validated by semi-structured interviews with BDA experts. The interviews are also used to customize and augment the framework for SMEs. Our findings indicate that whereas many BDACs dimensions are relevant for both large and small organizations, SMEs should devote attention to non-technical aspects of BDACs as well. Specifically, regarding the knowledge and resource constraints of SMEs, they require more outsourcing and external collaborations for developing BDACs. Our framework contributes to the research on digital transformation of SMEs in general, and specifically, to the assessment of their BDACs. The paper's practical implication lies in its usefulness for SME to successfully develop BDACs and to survive today's competitive environment.

Keywords: Small and medium-sized enterprises, big data, big data analytics capability, data analytics, assessment framework

INTRODUCTION

With the advent of digital transformation entailing in unprecedented and ubiquitous connectedness, all sorts of objects with sensors and trackers continuously generate and share new data (Tsai, Lai, & Vasilakos, 2014). The resulting huge increase in the amounts of data popularized the concept of big data. Though big data is sometimes regarded as the newest buzzword, the most influential IT innovations in the last decade are deemed to be related to big data (Wang & Hajli, 2017). Digital innovations such as business intelligence and customer targeting that enable services of unicorn companies like Uber and Airbnb rely heavily on big data.

With data becoming more important in businesses, data analytics no longer plays a role only in large organizations, but also in small and medium-sized enterprises (SMEs). By analyzing their data, firms can reveal hidden insights, make faster and better-informed decisions, and gain competitive advantage (Sharda, Delen, & Turban, 2014). That is why firms rank business analytic systems as their top technological priority (Papachristodoulou, Koutsaki, & Kirkos, 2017).

Nevertheless, most of the success stories about how data analytics transform businesses are anecdotal and are not supported by academic research (Gonzales, 2011; Gupta & George, 2016). Some academics even are skeptic about big data analytics (BDA) and consider it to be the newest vogue in management discipline (Matthias, Fouweather, Gregory, & Vernon, 2017). Their skepticism is reinforced by the large number of BDA projects that fail to deliver (Gupta & George, 2016). Since there is significant variation in the outcomes of data analytics efforts, the relationship between its use and the value it creates needs to be investigated to gain a better understanding of the underlying mechanisms (Chen & Nath, 2018). Generally, more data does not automatically mean that a company has more information and knowledge, and it only lead to better decisions and performance when the data is fully comprehended and properly analyzed (Matthias et al., 2017). Even if the data is analyzed well, firms still have to act on the obtained insights, for which many companies are not ready yet (Ross, Beath, & Quaadgras, 2013).

Despite its indisputable relevance, there is little existing research on how to develop BDA capability to exploit the potential of big data (Gandomi & Haider, 2015). The academic literature on BDA in SMEs is even scarcer (Llave, 2017). Most of the research on BDA that has been conducted hitherto focuses on the technical dimensions and issues of big data (Chen & Nath, 2018; Fosso Wamba, Akter, Edwards, Chopin, & Gnanzou, 2015). Nevertheless, many studies acknowledge the importance of investigating data analytics from a perspective that takes into account the managerial challenges and non-technical resources required to build BDA capabilities[1] (Chen & Nath, 2018; Gupta & George, 2016). Once a better understanding of how firms develop big data analytics capabilities (BDACs) is provided, the efforts to build BDACs will become more efficient and promising (Wang & Hajli, 2017).

One way to guide companies in developing BDACs is to evaluate their state of the capability with an assessment framework and specify actions that should be taken for improvement (Comuzzi & Patel, 2016). Several BDA assessment frameworks already exist, but many of them are created by consultancy firms and software vendors that do not reveal the methodology through which the model was created. Consequently, the internal validity of these models, which were ultimately

[1] In this research, Amit and Schoemaker's definition of capabilities is adopted, i.e. capabilities refer to "a firm's capacity to purposefully deploy a combination of resources and processes to achieve a desired goal" (as cited in Autio, George and Alexy, 2011).

designed with the purpose of selling a product, is questionable (Comuzzi & Patel, 2016). A few assessment frameworks were developed through academic research to overcome the validity issue, but they mainly focus on large organizations. This implies that these frameworks might not be suitable for SMEs to assess their BDACs, since their resources, sponsorship, and strategy for BDACs differ from large firms (Comuzzi & Patel, 2016).

This research is a first step to address the gaps in the literature and the practical needs for an assessment framework that is specifically designed for SMEs. The research question "which dimensions are relevant to build and assess big data analytics capabilities in small and medium-sized enterprises?" provides SMEs with information about important dimensions required to build and enhance BDACs. Such knowledge can increase the benefit of their BDACs and help them to prioritize their investment accordingly, making it more effective. Moreover, the answer contributes to academic scholarship about BDA in SMEs, which has heretofore received little attention compared to BDA in large organizations.

To answer this question, we first provide a description of the methodology for the literature review of existing BDA models, the design of the preliminary framework, and the interviews that were conducted. Subsequently, results from the literature review, the preliminary framework that resulted from the review and the interview results will be reported in the results section. This is followed by a discussion of the results and finally a conclusion.

RESEARCH METHODOLOGY

This research consisted of three consecutive phases. The first part was an extensive literature review that was conducted to discover dimensions that are relevant in a big data capability maturity model. The literature review included peer reviewed papers published in academic outlets, such as journal articles and conference proceedings, indexed by the Web of Science library. To do this, a search query was formulated with keywords and searched in the title, abstract, and keyword sections of the papers. The query used to execute the search strategy is a combination of three keywords with the first term being “big data”, the second “business” and the third “maturity”. As substitute for the first keyword we used “data analytics” and “data science”, for the second keyword “enterprise”, “firm”, “company” and “corporate”, and for the third keyword “measure” and “framework”. We reviewed the literature from 2007 onwards, as since then the influence of big data gained momentum in the academic communities. After this we identified a total 275 articles.

In the next step, one author independently scanned through the titles and abstracts of the articles to determine their relevance to the research endeavor. After this we were left with a dataset consisting of 47 articles. Each of the 47 articles that remained was now read by three of the authors in order to identify those articles that report on big data analytics capability. In doing so, we applied exclusion criteria. We excluded studies that were only marginally related to big data analytics capability. After completing this exercise, we consolidated the lists of relevant articles and discussed any disagreements. After this second round of exclusions we ended up with a corpus of 10 articles. These articles were reviewed by three researchers to identify dimensions that are relevant for a maturity model assessing SMEs’ BDACs. All the dimensions and subdimensions that were mentioned in these articles were listed per article in Microsoft Excel.

During the second phase of the research, these dimensions were analyzed and assimilated into a preliminary framework. The dimensions and subdimensions that had been collected were compared to combine similar dimensions from different articles. The elements were now sorted per article and per dimension by three of the authors, which facilitated analyzing whether dimensions reappeared in many articles or whether they were unique to one or a few articles.

Generally, a dimension that was included in many articles was considered to be more likely to be an important dimension of a BDAC. However, dimensions that did not appear in the majority of articles were not automatically disregarded, since these might indicate important elements that only a few researches have been able to uncover. Their relevance was discussed among the researchers and the dimensions were included or excluded accordingly. Furthermore, dimensions found in articles with a sound research methodology were preferred over dimensions from articles that were anecdotal, lacked a research description or that described research-in-progress.

In the ensuing step, the definitions of the dimensions were added to compare whether different authors meant the same thing with similar or closely related dimensions. This led to a new round in which similar subdimensions from different articles were categorized into overarching dimensions. Subsequently, a preliminary assessment framework was built from these dimensions by combining similar dimensions from several articles into one dimension and by assimilating associated subdimensions into dimensions of a higher order. In case a dimension was not found frequently in the reviewed articles, its source was evaluated and the inclusion of the dimension was discussed among the researchers to reach consensus.

In the third phase of the research, the assessment framework was improved and validated through semi-structured interviews with experts to determine whether it included irrelevant dimensions or whether relevant dimensions were missing. The inclusion criterion for interviewees (i.e. experts) was relevant expertise in (big) data analytics and or SMEs and the aimed sample size was six. The interview questions evolved partially from a template for expert review of maturity models created by Salah, Paige, & Cairns (2014). The first part of the interview was guided by 11 open questions. In the first part of the interview, some open questions were asked, such as "which dimensions/categories are relevant for a maturity model that assesses big data analytics capabilities of SMEs?". The aim of the open questions was to get the interviewee's opinion on topics related to the research without imposing specific views on them. During the second part of the interview, they were asked to evaluate the relevance of dimensions in the preliminary model that had not been mentioned yet in the first part. All interviews lasted between thirty minutes and one hour in total. Written notes of the interviewee's responses were made during every interview. Audio recordings were made if the interviewee gave consent to record the interview and if the setting allowed the interview to be recorded, which was the case in five interviews. These interviews were subsequently transcribed by one the authors in Microsoft Word. The analysis of the interviews was twofold. On the one hand, comments about the dimensions that were already included in the preliminary assessment framework were deducted from the notes and transcriptions. On the other hand, novel remarks that could not be related to one of the dimensions were also obtained from the data. The results were incorporated into the preliminary framework to design a final version of the dimensions for the maturity model that SMEs can use to assess their BDAC. The aim was to design a framework that was as parsimonious as possible while simultaneously being comprehensive.

RESULTS

In this results section, the first part is devoted to analyzing the results from the literature review. Subsequently, the preliminary assessment framework that resulted from the literature review will be described in the second section. The results from the interviews and their integration into the framework are the subject of the third part.

Literature Review of Maturity Models

Since the aim of this research is to discover relevant dimensions for an assessment framework to evaluate SMEs' BDACs, a literature review was conducted to analyze which related models have already been developed. Firstly, a brief background on the general structure and purposes of maturity models will clarify why they are suitable assessment frameworks. A maturity model is a useful framework for SMEs to analyze their readiness for BDA or for a next step in their BDAC, because it can help SMEs to decide whether they should invest in BDA depending on their business needs, but also whether they will be able to build a BDAC, since it requires substantial resources (Chen & Nath, 2018).

A maturity model is an instrument that facilitates an assessment of the level of capabilities and resources (Cosic, Shanks, & Maynard, 2012). The model identifies the different dimensions of the capability and the maturity levels that can be achieved within these dimensions (Comuzzi & Patel, 2016). When assessing a company's maturity level, a snapshot is taken of the dimensions and these are compared to the criteria to assess the right maturity level (Becker, Knackstedt, & Pöppelbuß, 2009). Maturity models have a descriptive and prescriptive purpose. The descriptive objective is to assess the current maturity of a capability. The prescriptive objective is to identify further levels of maturity and to provide guidelines to get the capability to this next level (Comuzzi & Patel, 2016; Cosic et al., 2012). Maturity models can be evaluated on their content, i.e. the appropriateness and validity of their dimensions, and on their usability, i.e. their completeness and ease of use (Salah et al., 2014). In this review, the content of relevant maturity models was analyzed to find common dimensions between the models. The names of the dimensions that where identified have been italicized for elucidation.

Comuzzi and Patel (2016) developed a Big Data Maturity Model by integrating existing maturity models from the industry into one model. They used a qualitative approach in which they analyzed the literature and interviewed domain experts. Their model contains the traditional five maturity levels of Humphrey (1988), which range from initial, repeatable, defined, managed to optimized and also has a level 0 for non-existent dimensions. Comuzzi and Patel's model contains five main dimensions and each of those has at least two subdimensions. The first dimension, *strategic alignment*, measures the alignment between the goals of big data projects and the overall organizational strategy. This dimension contains the subdimension *strategy* for the inclusion of big data in the organization's strategy and the subdimension *process* to assess the use of big data in the core business processes to achieve the strategy. The second dimension, *organization*, has the subdimension *people* to evaluate employees' awareness of the potential of big data and their knowledge about it. The other subdimension, *culture*, evaluates the extent to which the big data capability is trusted and considered to be important to the organizational culture. The *governance* dimension appraises the existence of formal organizational structures to define the management of the capability. At the core of their model are the *data* dimension and the *information technology* dimension. *Data* comprises the subdimension *management* to evaluate the maturity in addressing the big data lifecycle and the subdimension *analytics* to evaluate the scope of the analytics software and perceived ease of use. Finally, the *information technology* dimension includes the subdimensions *infrastructure* to measure the maturity of the IT environment and *information management* to evaluate the organization's perception on the structure of information resources.

Instead of a qualitative approach, Gupta and George (2016) ground their hierarchical model for measuring firms' BDACs in the resource-based view (RBV) of the firm. According to this theory, an organization is a collection of resources and by combining several different resources, organizations can generate a competitive advantage (Palmatier, Dant, & Grewal, 2007). Especially resources that are valuable, rare, inimitable, and non-substitutable (VRIN) create a sustained competitive advantage (Barney, 1991). Based on literature on big data challenges, Gupta and George propose seven resources for BDACs. These resources are internal and external *data* of various sizes, structures and speeds at which they are created; *technology* that can handle the challenges of big data; *basic resources* such as financial investments and time; *managerial skills* concerning an understanding of the ways in which extracted insights can be applied to business needs and the development of strong interpersonal relationships; *technical skills* regarding the required knowledge to use the technologies to extract insights from the data; *data-driven culture* in which decisions on all levels are based on extracted insights rather than intuition or experiences; *intensity of organizational learning* that depends on a firm's ability to reconfigure its resources to gain and apply new knowledge. These seven first-order constructs are combined into three second-order constructs: *data*, *technology* and *basic resources* are *tangible resources* that organizations can buy or sell in a market; *technical* and *managerial* skills are *human resources* consisting of employees' knowledge and abilities; and a *data-driven culture* and the *intensity of organizational learning* are *intangible resources* that are not easily bought or sold in markets and are heterogeneous across organizations, which means that most of them meet the VRIN status. These three second-order constructs are aggregated into one third-order BDAC formative construct. They validated their BDAC construct by assessing its relationship with firm performance. Both the market performance and operational performance were positively correlated to the firm's BDAC.

Cosic et al. (2012) developed a Business Analytics Capability Maturity Model (BACMM) for large-scale organizations with the design science research approach. They also draw upon the resource-based view and consider BA as a dynamic capability built by reconfiguring and renewing resources into a new capability. The more mature this BA capability, the greater the value and competitive advantage. In accordance with Becker et al.'s (2009) design science approach, they defined the problem, compared it to existing maturity models, and determined their development strategy. The BA capabilities that resulted from a systematic literature analysis were categorized with thematic content analysis. They identified sixteen lower level BA capabilities that were combined into four BA capability areas based on their similarities.

The first category in Cosic et al. (2012) model is *governance*, which is the mechanism for managing the usage of BA resources in an organization. Its lower capabilities are *decision rights* to determine who the decision-makers are and to hold them accountable; *strategic alignment* between BA initiatives and organizational strategy; *dynamic BA capabilities* to continuously renew resources to respond to changing business environments; and *change management* to manage the acceptance and embracement of technological changes by reducing risks and providing training as lower capabilities. Secondly, *culture* are the tacit and explicit norms, values and behavioral patterns that lead to data collection and analysis. Culture encompasses as capabilities the *evidence-based management* of cultures in which decisions based on data supersede reputation and intuition; *embeddedness* of BA in employees' values and daily routines; *executive leadership and support* for the increased use of BA systems and data-driven decision-making; and *flexibility and agility* as the level of change readiness of the organizational culture. The third area, *people,* refers to all employees who use BA with *technology knowledge and skills* of BA technology specialists; *business knowledge and skills* of BA business specialists; *management knowledge and skills* of management responsible for BA projects; and *entrepreneurship and innovation skills* of employees using BA to develop innovative and effective processes and products that increase performance and competitive advantage as lower capabilities. Lastly, *technology* is the area that concerns the development and usage of hardware, software and data in BA. It encompasses *data management* of an integrated, high-quality data resource; *systems integration* of BA systems with operational systems; *reporting and visualization BA technology* to show results in an understandable format to address routine problems; and *discovery BA technology* to identify correlations and patterns for forecasting. Though Cosic et al. (2012) consider diverse capabilities, they emphasize that the model is still in progress and needs to be enhanced.

Another study from the perspective of RBV was conducted by Akter Fosso Wamba, Gunasekaran, Duby and Childe (2016), who created a hierarchical model of a BDAC. Besides the RBV, they also draw on the sociomaterialism perspective. According to sociomaterialism, social and material dimensions are intertwined, which means that the organizational, physical and human dimensions act together instead of isolated. Hence, each distinct dimension supports and reinforces the others. Their literature review revealed three higher-order dimensions of a BDAC: *management*, *technology* and *talent capability*. The subdimensions for the three primary dimensions were identified with two Delphi studies. The *management capability* included *planning* for identifying opportunities and determining how BDA enhances performance; *investment decisions* reflecting cost-benefit analyses; *coordination* for a routine capability and cross-functional analytic activities; and *control* by ensuring proper commitment and usage of resources. The *technology capability* included *connectivity* among departments to collect and analyze data from various sources; *compatibility* for continuous flows of information; and *modularity* indicating flexible platform development. The *talent capability* contained the *technology management knowledge* for managing knowledge about big data resources to achieve business goals; *technical knowledge*, such as knowledge about databases and operational systems; *business knowledge* for the understanding of the business environment and its different departments; and *relational knowledge* as the ability to communicate and collaborate with employees from other functions. Akter et al. confirmed that BDACs have significant impact on firm performance.

In their research, Wang and Hajli (2017) propose a big data analytics-enabled business value model by using the RBV and the capability building view. The capability building view compensates for weaknesses of the RBV, because the RBV draws criticisms that it is does not explain how resources should be arranged and how unique capabilities, leading to competitive advantages, can be created from IT systems. According to the capability building view, inputs are transformed into valuable outputs when a company effectively selects, redistributes and combines resources (Karimi, Somers, & Bhattacherje, 2007; Wang & Hajli, 2017). Based on the RBV, Wang and Hajli consider the BDA architecture as a technical resource with three components: *data aggregation* for data generation and aggregation through acquisition, transformation and storage; *data processing* for appropriate descriptive, predictive and prescriptive analyses; and *data visualization* for generating output. In line with the capability building view, these three components all produce BDACs that subsequently create business value. However, Wang and Hajli do not consider non-technical components of BDACs.

Another approach is taken by Alharthi, Krotov and Bowman (2017), who address barriers to big data and categorize these barriers with a solution into three dimensions: *technology, people*, and *organization*. A review of these barriers is relevant for the development of a maturity model, since the barriers identified in this paper indicate components that are necessary for a BDAC. These barriers need to be overcome to leverage big data for improvement of organizational performance. In the *technology* dimension, the *infrastructure readiness* is a barrier due to significant hardware and software investments; and the *complexity of data* is a problem because of the rate of data growth and the multiple sources and formats of data. The *human barriers* are a *lack of skills* in big data and analytics and *privacy* of personal data that causes legal and ethical challenges. The *organizational* barrier is the *organizational culture*, because the strategy is based on the organizational norms and a lack of understanding of the value of big data can lead to resistance to big data adoption.

Closely related to this approach of identifying barriers is the method to find organizational capabilities that are important for big data readiness. Klievink et al. (2017) combined similar capabilities from a literature review through content analysis into an assessment framework with seven capabilities for using big data: *IT governance* refers to developing an IT strategy and structures for decision-making and assigning responsibility; *IT resources* to design a suitable infrastructure and have adequate expertise, *internal attitude* towards data-driven decision-making; *external attitude* of stakeholders to support new systems; *legal compliance* regarding privacy protection, security and data ownership regulations; *data governance* refers to developing a data strategy, such as acquisition and quality control; and *data science expertise* implies developing or acquiring the required data science knowledge. Gonzales (2011) takes a different approach by identifying success factors that influence the maturity and competitiveness of BI and data warehousing (DW) initiatives. His preliminary model contains four key factors: *leadership* for a sound strategy with the subordinate variables *sponsorship* of BI/DW, *organization* to encourage the use of BI/DW, and *planning* to align the BI/DW strategy with the organizational strategy; *skill* with the subordinate variables *user competencies* and *training*; *infrastructure* from a technical perspective, such as the *hardware* and *software components*, and from a functional perspective, such as the *development standards*, *metadata* and *data quality*; and *value* with the variables *financial commitment* that is dedicated to BDA initiatives, *risk* that refers to reducing resistance and fostering cooperation; and *contribution* for the role BI/DW plays in reducing costs and enhancing value. Since Gonzales' results are only preliminary findings, more validation of these factors is required to verify their adequacy in assessing BDA maturity.

Besides these maturity models that address large organizations, a few measurement frameworks have been developed for SMEs. A review of these frameworks gives an indication of relevant dimensions for SMEs. Hidayanto, Kristianto and Shihab (2012) created a framework to assess SMEs' readiness of BI implementation. They identified 18 success factors from the literature. These are elements that an organization needs to achieve its mission. They applied the analytic hierarchy process to select the best alternative from multiple criteria. The first level of the model is BI implementation readiness. On the second level are three categories that group the readiness factors that were adopted from the critical success factors. The *organizational* category includes *committed management support and sponsorship* to make necessary resources available; *clear vision and well-established business case* to guide the implementation of BI; *strategic alignment* between business and IT strategies; *effective business/IT partnership for BI* refers to effective use of IT to improve business results*; BI portfolio management* to review and rank business impacts and risks of investments; *continuous process improvement culture* to get value from BI; *culture surrounding the use of information and analytical applications* means embracing BI to improve business results; *cross-organizational collaboration culture* to integrate knowledge about customers, competitors and the market; *decision process engineering culture* in which structured decision processes are used to make recurring decisions more effective.

Hidayanto et al. (2012) *process* category has the factors *business-centric championship and balanced team composition*, which means to have an advocate for BI from the business side and to have a cross-functional team with technical and business employees; *availability of skilled member team* requiring enough experience in BI; *businessdriven and iterative development approach* means that BI projects should be business-oriented and planned and scoped to be more flexible to changing requirements; *user-oriented change management* to communicate the demands and expectations of users to make BI successful. The third category, *technology*, includes the factors *business-driven scalable and flexible technical framework* conforming dynamic business needs; *sustainable data quality and integrity* for successful BI system implementation; *importance of metadata* to understand the context of data; *BI and DW technical readiness,* such as the network infrastructure and readiness for analytic tools; and the *silver bullet syndrome,* which implies to strive for the lowest possible number of tools. The readiness of a factor is evaluated on levels 0 to 3 that range from none, small degree, some degree to adequate degree. Hence, this model deviates from the typical five levels.

Coleman et al. (2016) propose a big data maturity model for SMEs that helps in the effective implementation of big data projects. They analyzed maturity models developed by large players in the big data field that provide consultancy services or sell software, such as IBM, IDC and SAP. A comparison of these models resulted in seven dimensions for assessing the maturity of big data adoption. These dimensions are *business strategy* for the extent to which the business strategy is considered when developing the data analytics infrastructure; *data management* refers to the efficiency of data collection, storage and retrieval of internal and external sources; *existence of specialized people and analytical skills* are the skills and knowledge about effective implementation of big data projects; *technological infrastructure* is the hardware architecture for data collection, storage and transmission; *level of enterprise adoption* is the extent of company engagement in data-centric management, ranging from local to enterprise-wide; *leadership and corporate culture* refers to the support and motivation from the leadership and culture for data analytics; and *data governance* refers to the existence of policies for distribution and usage of data and access to information to address security, privacy and ethical issues. They relate each of these dimensions to multiple challenges that SMEs face to make effective use of big data. The majority of these challenges have been discussed previously in this paper, but Coleman et al. (2016) do not tailor their maturity model to address these challenges nor do they provide specific guidelines for SMEs to overcome these challenges. Therefore, more research needs to be done here.

Collectively, these studies were considered to provide an extensive overview of possibly relevant dimensions for assessing SMEs' BDACs. They approached BDA from different perspectives, such as the RBV or barriers to BDA adoption, and applied various research methods. Subsequently, these dimensions were analyzed and assimilated into the preliminary assessment framework that will be presented next.

Preliminary Assessment Framework

The preliminary framework is a three-level hierarchical model that was constructed from dimensions in the literature review. Dimensions from past literature were sorted and combined based on similarity in the second and third phase of the research. A more thorough explanation of this process can be found in the methodology. The hierarchical structure of the model has been visualized in Figure 1. On the first level, the preliminary framework contains the four dimensions *tangible resources, intangible resources, governance,* and *strategy*. These dimensions can be presented in a framework similar to that of Mikalef, Framnes, Danielsen, Krogstie and Olsen (2017) with resources and enablers. In this research, the dimensions *governance* and *strategy* are considered as enablers of BDA. This framework has been visualized in Figure 2.

Insert figure 1 and 2 about here.

The dimension *tangible resources* contains the resources that are available for purchase and selling in the market (Gupta & George, 2016). Its first subdimension is *data collection* to evaluate the identification of data types and sources. *Data collection* contains two subdimensions: *data sources* with *data extraction from internal operational systems* and *data extraction from external* *sources* as components, and *data types* with historical, *real-time, structured, unstructured, big data* and *metadata* as its components. The second subdimension of *tangible resources* is *data analytics* to describe the understanding and analysis of data for knowledge extraction (Comuzzi & Patel, 2016). *Data analytics* includes the subdimension *analytics types*, which has in turn three components: *descriptive, predictive*, and *prescriptive*. *Data analytics* also comprises the subdimension *analytics tools* with *statistical and datamining software* and *reports, dashboards, scorecards, OLAP, visualization technologies* as components (Cosic et al., 2012). Another subdimension of *tangible resources* is the *data architecture* with the components *data storage, processing, integration, transformation,* and the *relationship between the data structure and analytics tools*. The last subdimension of *tangible resources* is the *technology infrastructure*, referring to the maturity of the organization's IT for the acquisition, management, and extraction of knowledge from data (Comuzzi & Patel, 2016). *Technology infrastructure* includes *central data warehouse, systems integration, security of the infrastructure* and *user access* as components.

The second dimension of a BDAC is *intangible resources*, which are resources that are less easily acquired and are therefore more heterogenous across companies (Gupta & George, 2016). *Intangible resources* includes the *culture* of the organization as subdimension. *Culture* encompasses five components. Firstly, it includes a *data-driven culture* in which decisions are based on data instead of intuition (Pfeffer & Sutton, 2006). The second component is *leadership support for BA* to promote the use of data in decision-making (Davenport, Harris, & Morison, 2010). Thirdly, *flexibility and agility* assesses the organization's responsiveness to changes in the business environment (Cosic et al., 2012). Furthermore, *culture* covers *trust in employees' BDA talents* to stimulate individuals to use BDA and lastly *an organizational vision for cultural change* to make the change to big data successful (Bumblauskas, Nold, Bumblauskas, & Igou, 2017). The other subdimension of *intangible resources* is *human resources* with the subdimension *people* for *employee involvement* to assess employee engagement with BDA (Comuzzi & Patel, 2016). *Human resources* also has a subdimension for *skills and competences*. The *skills and competences* that are deemed relevant are *technology skills and knowledge*, *business skills and knowledge*, *management skills and knowledge*, *innovation skills,* and *communication skills*. Finally, the subdimension *skills and knowledge* includes *training* to teach missing data analytics and big data skills (Miller, 2014).

The third dimension is *governance*, which is the mechanism for assigning authority and control over the BDAC (Comuzzi & Patel, 2016; Cosic et al., 2012). *Governance* has a subdimension *analytics governance* with the subdimension *process*. Within *process,* the component *BDA control* assesses whether an organization has clear performance criteria and monitors performance (Fosso Wamba et al., 2017) The component *legal compliance* evaluates the organization’s strategy regarding privacy, security and data ownership (Klievink et al., 2017). The other subdimension of *analytics governance* is *structure*, which evaluates the *decision rights* to determine who can make which decisions and *coordination* to assess cooperation between different departments of the organization (Weill and Ross, 2004; Fosso Wamba et al., 2017). The second subdimension of *governance* is *IT/data governance,* which assesses the *IT governance* and the *data governance* that the organization has in place to control and to develop policies for IT projects and data management (Spacey, 2016).

The fourth dimension is *strategy*, which assesses the *sponsorship by top management team* for BDA projects. It also includes *planning* to assess the organizational changes in BDA objectives in congruence with changing organizational objectives (Gonzales, 2011). Furthermore, *strategy* should evaluate whether an organization implements *change management* to help employees with accepting new technologies and to reduce resistance (Anderson-Lehman, Watson, Wixom, & Hoffer, 2004). Moreover, the model considers as components of *strategy* whether the use of BDA is reconciled with the organizational structure in *organizational alignment* and whether the type of BDA tools and the BDA activities they support is defined with the component *IT strategy alignment*. Furthermore *strategy* contains a subdimension *value* with *financial commitment* to measure funding, *risks* to identify resistance while fostering cooperation, and *contribution* to assess the value that BDA adds to the organizational value (Gonzales, 2011).

Interview Results

Together, these dimensions composed the preliminary assessment framework that was validated by interviews. Eight semi-structured interviews were conducted with professors and professionals with expertise in the field of (big) data analytics and/or SMEs. Table 1 provides an overview of the job title of each interviewee accompanied by a brief description of their function.

Insert table 1 about here.

The interviewees' responses to the relevance of the dimensions were summarized as 'yes' and 'no' responses. In case the interviewee deemed a dimension to be relevant, 'yes' was recorded, but when the interviewee did not consider a dimension to be relevant, 'no' was recorded. Nothing was recorded if the interviewee talked about the dimension, but did not give a clear opinion on its relevance, or the dimension was not addressed in the respective interview. Sometimes, certain dimensions were not discussed because they did not belong to the interviewee's area of expertise. The most interesting results were the 'no' responses, because they implied that interviewees considered a dimension to be irrelevant, redundant or inaccurate, whereas confirmative responses merely reinforced that dimensions found in the literature are also relevant to assess SMEs' BDACs.

Furthermore, dimensions that received nearly no responses could indicate that these dimensions are less important in assessing SMEs' BDA maturity, though this did not need to be the case necessarily. The dimensions that were considered to be irrelevant by a few interviewees or only received a few responses were reconsidered to improve the validity and usefulness of the model. Additionally, interesting results were dimensions that were mentioned, but that were not part of the preliminary framework.

The responses were analyzed per dimension to identify their relevance or irrelevance and decide on their inclusion or exclusion accordingly. For the *tangible resources*, the responses can be found in Table 2. The average response rate for these dimensions was 5.1. *Historical data* was only mentioned explicitly by two interviewees, who agreed on its relevance. The dimension was retained despite the low number of responses, because other interviewees referred to it indirectly when talking about *data extraction from internal operational systems* and *descriptive* analytics. Interviewee 6 commented that the importance of data for the digital revolution is similar to that of oil for the industrial revolution. All interviewees responded to *big data*, but interviewee 2 did not consider this to be a relevant dimension, because he believed that most SMEs are not ready for big data and that they do not have time to invest in it. Other interviewees acknowledged that big data might be challenging for SMEs. For example, interviewee 8 mentioned that big data is like a black box to SMEs, because they do not understand the internal workings. Nevertheless, the other interviewees considered big data to be relevant for SMEs and outweighed the opinion of interviewee 2. *Predictive* analytics received a negative response from interviewee 1 and *prescriptive* analytics from interviewees 1 and 2, because they thought these dimensions are too complicated and irrelevant for SMEs, but their responses were outweighed by other interviewees who see possibilities for SMEs in these dimensions. Corresponding to his negative responses to the advanced analytics types, interviewee 1 also answered ‘no’ to the dimension that concerns *statistical and data mining software* for conducting advanced analytics.

Insert table 2 about here.

Furthermore, *data processing, data integration* and *data transformation* were all negated by interviewee 2, who claimed that SMEs, with few exceptions, do not have knowledge about *data architecture* and instead usually outsource this. Other interviewees also recognized the importance of outsourcing when the SME lacked the knowledge. However, a lack of knowledge about *data architecture* does not imply its irrelevance, which means that the dimension was retained. The *relationship between the data structure and analytics tools* received only two responses, of which the response from interviewee 2 was negative for the above-mentioned reason. In hindsight, this relationship appeared to be inherent in the other dimensions in *data architecture* that received more responses, which means that it was redundant and could be discarded from the framework. Opinions on the importance of a *central data warehouse* differed. Whereas three interviewees considered this to be relevant, two interviewees (2 and 3) disagreed. According to interviewee 2, a relational database is sufficient for SMEs and interviewee 3 thought that a scalable cloud solution is the best option for SMEs. Interviewee 5 also observed a trend in software and storage in the cloud. Hence, *central data warehouse* appeared to be an inaccurate dimension and a *suitable data storage solution* covered this dimension better. *Systems integration* and *user access* were considered to be irrelevant by interviewee 2, because he thought that SMEs are already happy if their systems function well and they are not going to tinker with it if that is not necessary. However, since well-functioning systems were considered to be well-integrated and required appropriate access, these dimensions were maintained.

In Table 3, the responses for dimensions in *intangible resources* have been recorded. On average, the response rate for these dimensions was 5.6. Though *data-driven culture* received many positive answers, interviewee 3 answered ‘no’, because he thought that SMEs require a collaborative culture instead of a data-driven culture. The potential relevance of a collaborative culture was documented, but this did not exclude the relevance of a *data-driven culture*, which was therefore maintained in the framework. Though the relevance of *leadership support for BA* was confirmed, interviewee 8 remarked that owners cannot devote a lot of attention to BDA, because they have cognitive limitations due to the many things they have to do. Interviewee 3 reinforced this by noting that despite the importance of support, owners already have a lot of responsibility and do not want to add something else. On the other hand, interviewee 6 considered support as the driver behind everything. *Flexibility and agility* were considered as an advantage for SMEs over large organizations by interviewees 3, 5 and 6, because SMEs can switch faster and easier due to their size. Interviewee 6 thought agility is essential to prevent being overrun by large organizations.

Insert table 3 about here.

For *technology skills and knowledge*, interviewee 8 noted that it can be problematic, because many SMEs do not have an IT professional nor money to hire someone. According to interviewee 2, owners should go onto the work floor to listen to employees’ ideas for *employee involvement*. *Management skills and knowledge* also received many confirmative responses against one negative response from interviewee 1. He considered professional knowledge in a certain field to be required more for BDA than management skills. He compared a good collaboration between employees with technical and business knowledge to a two-stage rocket. However, the type of knowledge he referred to was already covered in the dimensions *technology* and *business skills* and *knowledge*. Moreover, specialized professional knowledge does not preclude the importance of *management skills* and *knowledge*, as was recognized by the majority of interviewees. Lastly, interviewee 8 considered *training* to be an issue for SMEs, because they cannot afford a lot of slack. If a few employees cannot be on the work floor due to trainings, it can already have a large impact on the daily business of SMEs. Nevertheless, this remark related to the time constraints of SMEs instead of the importance of *training*.

As Table 4 illustrates, the responses to subdimensions in the *governance* dimension were unanimously positive, which means that the interviewees agreed to the relevance of these dimensions in assessing BDAC maturity in SMEs. However, the number of responses given per dimension was 4.2 on average, which was lower than the average amounts given for dimensions of *tangible resources* and *intangible resources*. One reason for the low response rate was interviewee 2 who abstained completely from assessing the dimensions in *governance*, because it was not her area of expertise and she did not consider herself to have the required knowledge to give a substantiated opinion on them. Furthermore, only one response could be noted for interviewee 6 due to time constraints, but he considered *governance* in general to be relevant in bringing together data and people from different disciplines. Consequently, four positive responses were given for *BDA control*, six for *legal compliance*, four for *decision rights* and *coordination*, three for *IT governance* and four for *data governance*. Though *legal compliance* was regarded as essential, interviewees also saw it as problematic for SMEs. According to interviewee 5, SMEs' legal compliance is like the 'Wild West' with little control and coordination. In the opinion of interviewees 2 and 3, the GDPR worsens legal compliance issues and could even be a barrier to enter data analytics. Moreover, interviewee 3 mentioned that too much *BDA control* impedes analytics and innovation.

Insert table 4 about here.

The response rate for the dimensions in *strategy* was the lowest with 3.6 on average, which was mainly caused by only one response for the dimensions *financial commitment* and *risk*. The responses for each interview can be found in Table 5. The low number of responses was not consistent throughout the dimension. *Sponsorship of top management team* and *contribution* received seven and six positive responses respectively. However, it was noted that the responses for *sponsorship of top management* were very similar to those of *leadership support for BA*. To enhance the parsimony of the model, these dimensions were merged into *support and sponsorship from management* and placed under *culture* because of the more informal nature of SMEs. *Planning*, *organizational alignment* and *IT strategy alignment* got a negative response from interviewee 2. Interviewee 1 also answered negatively to *planning* and interviewee 8 doubted between ‘yes’ and ‘no’ for *planning* for similar reasons, i.e. SMEs do not plan their strategy. According to interviewee 2, planning a strategy causes inessential bureaucracy for SMEs and interviewee 8 mentioned that it often depends on the size of the SME whether its strategy has been formally defined. Generally, small SMEs (<50 employees) are less likely to have a clearly defined strategy than larger SMEs. On the other hand, interviewees 1, 3, 5 and 7 considered that planning and alignment of strategy are either the case or that they are important.

Insert table 5 about here.

Interviewee 3 thought it helps to understand the possibilities of BDA and distinguish ‘science fiction’ (what people think BDA can do) from reality, which in turn reduces risk. Since these dimensions received a lot of positive responses, they were still regarded as relevant, but because the interviewees disagreed about the extent to which SMEs have their strategy planned, three separate dimensions were considered as too much. Therefore, they were merged into one dimension *strategic alignment*.

Change management got only two responses, because many interviewees were either not explicit in their answer or were unsure about this dimension. As interviewee 3 remarked, SMEs are much more flexible to change quickly due to their small size. This indicates that SMEs’ *flexibility and agility* makes *change management* redundant and it was therefore removed. Finally, *financial commitment* and *risks* both only received one response. This indicated that they were not mentioned as subdimensions of *value*, contrary to *contribution*. However, except interviewee 2, every interviewee talked indirectly about *financial commitment* by discussing financial constraints for SMEs. Interviewees did not talk about *risk* in terms of resistance and cooperation. To improve the parsimony and understandability of *value*, only the subdimensions *financial commitment* and *contribution* were maintained. Interviewees 3 and 4 believed that potential *contributions* of BDA are improved efficiency and increased competitiveness. In the opinion of interviewees 2 and 6, SMEs have to be sure that BDA will deliver returns before they invest and they also require returns quicker than large organizations. Interviewee 2 believed that initial successes will create a hunger to do more with data and value will then arise stepwise.

Moreover, several elements reappeared in the interviews that had not been included in the preliminary assessment framework. These elements are added as *additional dimensions* in Table 6. *Outsourcing* and *external collaboration* were mentioned by five interviewees. SMEs could outsource data analytics and/or the technical infrastructure, depending on the skills and knowledge they lack. According to interviewee 6, trying to hire an expert is similar to trying to hire Cristiano Ronaldo (i.e. a famous football player). They are seen as superstars, which means that they are unattainable to SMEs. Therefore, outsourcing analytics instead of hiring someone is an alternative. Interviewee 3 even mentioned outsourcing to ensure legal compliance. Since *outsourcing* is a strategic choice, the dimension was added to *strategy* with the components *technology* and *labor*. *External collaboration* between SMEs in the same industry and from different industries was deemed important to share expertise and spread the risk of investing in BDA. Interviewee 6 mentioned the importance of knowing who the other SMEs in the ecosystem are and interviewee 8 remarked that networking and coordination are essential for successful collaborations. Therefore, *external collaboration* was added to *structure* with the components of *external collaboration* are *identification of other SMEs*; *collaborate with SMEs in same industry*; *collaborate with SMEs in other industries*. Two interviewees mentioned *data quality management* and *ethics*. Though *data quality management* was considered a component of *data governance* by the researchers, this might not have been explicit enough. Therefore, *data quality management* was added as subdimension of *data governance*. Finally, interviewees indicated the relevance of *ethics*. Interviewee 8 considered *ethics* as a potential non-financial goal of SMEs and interviewee 2 believed *ethics* is important when working with data about people. Hence, *ethics* was added as subdimension of *process* in *analytics governance*. Figure 3 visualizes the hierarchical framework after the adaptations based on the interviews.

Insert figure 3 and table 6 about here.

DISCUSSION

In this section, the preliminary framework and the results from interviews will be discussed by contrasting them to existing research. Moreover, it will be discussed which new knowledge has been discovered and how this addresses the identified gaps in the literature at the start of this paper. To obtain reliable results, the methodology of this research was comparable to other studies and the approach that was adopted for designing the assessment framework bears resemblances to previous work. Similar to Klievink et al. (2017), the results from the literature were analyzed on content and comparable to Comuzzi and Patel (2016), the framework was evaluated with interviews. Furthermore, the framework is based on the RBV, which is congruent with previous studies by Gupta and George (2016), Cosic et al. (2012), Akter et al. (2016) and Wang and Hajli (2017). However, the dimensions in their models were not considered to be exhaustive. Many models from the literature included different dimensions and no model included all the dimensions covered by the framework developed in this research. For example, the model from Wang and Hajli (2017) merely considered resources in the technical dimension and the models from Gupta and George (2016) and (Akter et al. (2016) did not encompass governance, even though governance has been identified as an enabler of BDACs (Mikalef et al., 2017). A plausible explanation for this finding is that these studies only reviewed limited literature. For instance, Coleman et al. (2016) and Comuzzi and Patel (2016) reviewed models from the industry, Alharthi et al. (2017) and Gupta and George (2016) reviewed literature about big data challenges, and Hidayanto et al. (2012) and Gonzales (2011) identified success factors from the literature. However, none of the reviewed studies integrated all this literature. This research attempted to overcome this deficiency by integrating all these dimensions from the different studies into one all-encompassing framework, which was then validated by interviews.

During the interviews, many non-technical dimensions were considered relevant by the interviewees. This supports the remark that there is more to BDA than just the technical side (Fosso Wamba et al., 2015; Akter and Fosso Wamba, 2016; Chen and Nath, 2018). Therefore, this research reinforces that SMEs should also devote attention to their culture, human resources, governance and strategy. Similar to prior research, interviewees also recognized that SMEs' BDACs are in certain respects different from those in large organizations. For instance, SMEs' size is advantageous for flexibility, but disadvantageous for legal compliance, because they are less likely to have legal knowledge (Sen, Ozturk, & Vayvay, 2016).

Besides the relevance of dimensions that were obtained from the literature, SME specific dimensions surfaced during the interviews. A common theme that merged was that SMEs should outsource the parts of their BDAC for which they neither have sufficient financial resources nor the required knowledge to develop it internally. This finding is in line with Alshamaila, Papagiannidis and Li (2013), who stated that many companies outsource their IT to improve its effectiveness, and Gutierrez, Orozco and Serrano (2009), who argued that especially SMEs tend to do this. However, none of the studies in the literature review contained a dimension for outsourcing, regardless of the company size considered. Nevertheless, the interviews revealed it is relevant and therefore it is included in our BDAC SME assessment framework. Moreover, outsourcing analytics tasks could be an affordable alternative to hiring an expert, since the scarcity of people with the required technical expertise makes them too expensive for SMEs (Coleman et al., 2016).

Another theme that reappeared in multiple interviews was the need for SMEs to collaborate. Cross-organizational collaboration was part of Hidayanto et al. (2012) model, but this concerned collaboration between different departments within one organization. The interviewees in this research considered that SMEs should collaborate with other SMEs. This enables them to divide BDA tasks based on the SME's knowledge and all enjoy the benefits, while simultaneously sharing the expenses and spreading the risks. These last two elements are important, because interviewees emphasized SMEs' limited financial resources, which has also been recognized by Coleman et al. (2016). Moreover, BDA projects already often fail in large organizations with sufficient financial resources, not to mention SMEs with constrained resources (Asay, 2017). Collaboration between SMEs could mitigate these problems. The potential value of collaborative SME networks has been recognized by researchers in multiple fields (Antonelli, Bruno, Taurino, & Villa, 2015; Fornasiero & Zangiacomi, 2012; Robson & Bennett, 2000). However, to the best of the author's knowledge, no research has been conducted on SME collaboration in BDA.

Hence, this research contributes to the current knowledge about building and assessing BDACs by extending and adapting an assessment framework to the area of SMEs. Consequently, it was discovered that many dimensions that are relevant for large organizations are also relevant for SMEs, but SMEs should resort to outsourcing and collaborating where their limited knowledge and resources obligate them to do so. Moreover, this research has practical implications for SMEs, because the framework can help them to identify which relevant dimensions they should develop for a BDAC. Based on these relevant dimensions, SMEs can assess their needs and readiness for a BDAC to avoid investing in projects that do not deliver expected returns.

However, the assessment framework developed in this research requires further research. Due to the limited scope and time frame of this research, only interviewees who are employed in the Netherlands were interviewed. The position of SMEs in the economy or the stance towards outsourcing and collaborating could be different elsewhere, which means that the results cannot be generalized to SMEs in other countries. Therefore, future research could take a more international perspective. Furthermore, outsourcing and collaboration were addressed in several interviews, but more research is required to examine how they will actually contribute to building a BDAC.

A methodological limitation is that the validation of the assessment framework is based entirely on qualitative data. The results might be biased due to the phrasing of the questions, even though it was attempted to ask open question that are not leading. Besides, the interviewees all had expertise in BDA, which means they might hold an over-optimistic opinion on the importance of a BDAC for SMEs. This issue could be overcome in further research with a mixed-methods approach by combining the current results with quantitative data being more objective.

Moreover, the results from a quantitative study could be used for the development of the maturity model. To actually assess the maturity of SMEs' BDACs on a greater scale and to give insights into what can be improved to enhance maturity, the framework that resulted from this research needs to be developed into a maturity model. To complete the model, further research should determine the amount of maturity levels and the dimensions at each level. The prevailing number of levels used by researchers is five (Becker et al., 2009). However, the researchers recognized that this might be too many different levels for SMEs. Furthermore, it needs to be decided how the maturity levels will be represented. In a staged model, organizations need to have all dimensions at a preceding level to be able to move to a higher level, whereas different dimensions can be at different maturity levels in continuous models (Van Steenbergen, Bos, Brinkkemper, Van de Weerd, and Bekker, 2001). Contrary to staged and continuous models, focus area models do not have a fixed amount of maturity levels, but instead specific maturity levels are defined for each dimension (Van Steenbergen, Van den Berg, & Brinkkemper, 2007). The choice of representation is beyond the scope of this research, but it will have implications for the assessment method.

Furthermore, future research could investigate the possibilities for SMEs to outsource and collaborate beyond the context of BDACs. Salvato and Rerup (2010) argued that breaking capabilities down into their components helps to understand their internal functioning and impact. This research discovered that outsourcing and collaboration are two components of BDACs. If other research would reveal that they are also components of other capabilities, they could possibly be important for developing SMEs' capabilities in general. Additionally, digital transformation and big data have led SMEs to experiment with traditional business models (Bouwman, Nikou, Molina-Castillo, & De Reuver, 2018). Therefore, future research could investigate whether outsourcing and collaborating play a role beyond BDA in other aspects of SMEs' innovative business models. These insights would create new knowledge about capability development and digitalization in the context of SMEs.

CONCLUSION

This paper discussed the first part of the development of a maturity model for assessing SMEs' BDACs. Though BDAC is important for SMEs to gain competitive advantage and keep up with large organizations, no comprehensive model aimed at SMEs has been designed yet. This research identified that many relevant dimensions for BDACs of large organizations are also relevant for SMEs. However, the size of SMEs' leads to some differences. On the one hand, it makes them more flexible, but on the other hand, it means that they have less knowledge and financial resources. Outsourcing and external collaborations emerged as potential solutions to these issues. These findings, in combination with relevant dimensions from previous models, can be used by SMEs in practice to identify relevant resources and assess their readiness for a BDAC accordingly.

Future research could investigate whether outsourcing and external collaboration also have implications for developing other capabilities in SMEs or whether they play a role in their digital transformation. Moreover, the assessment framework that is the result from this research can be processed into a maturity model that SMEs can deploy to assess the current level of their BDAC and to gain insights into approaches to improve their BDAC.

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FIGURES AND TABLES

FIGURE 1
Hierarchical Representation of the Preliminary BDAC Assessment Framework

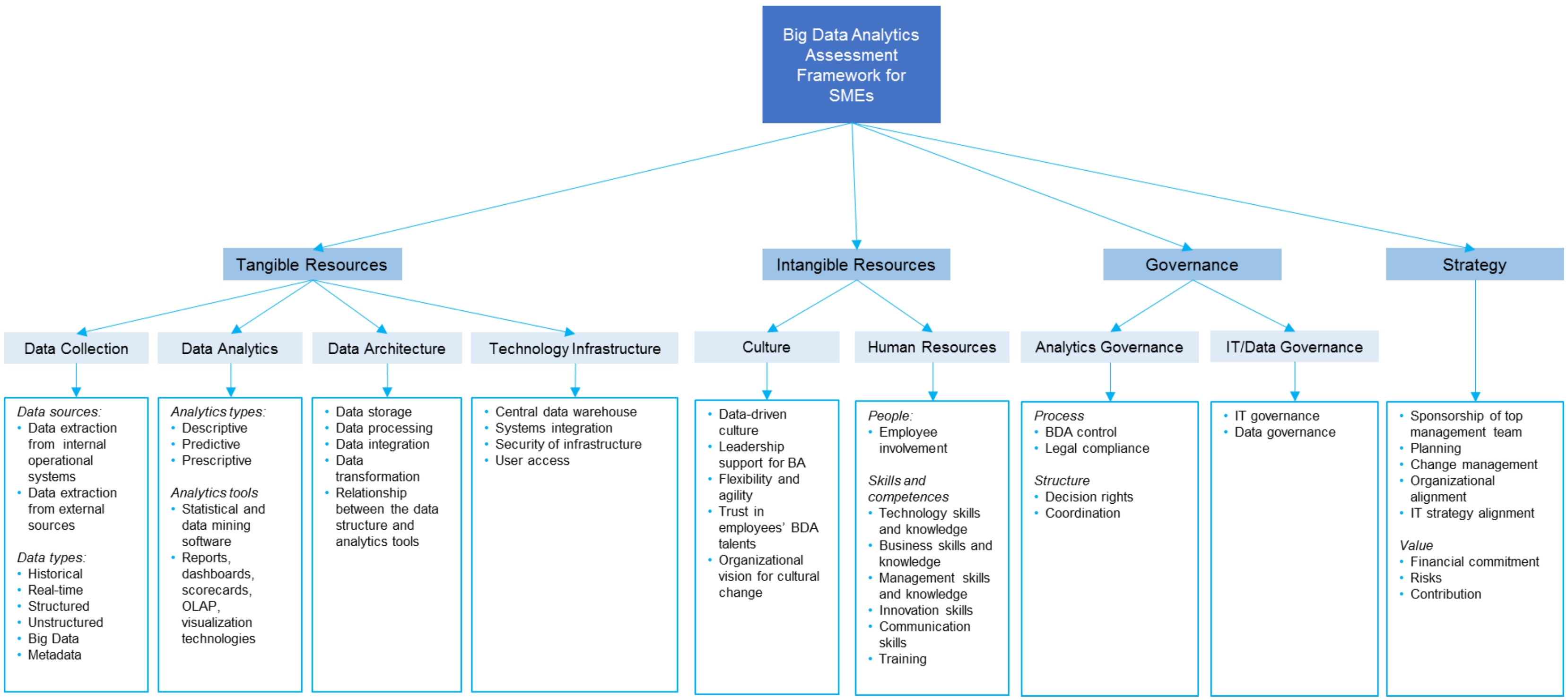

FIGURE 2
Conceptual Framework of Dimensions Constituting a BDAC

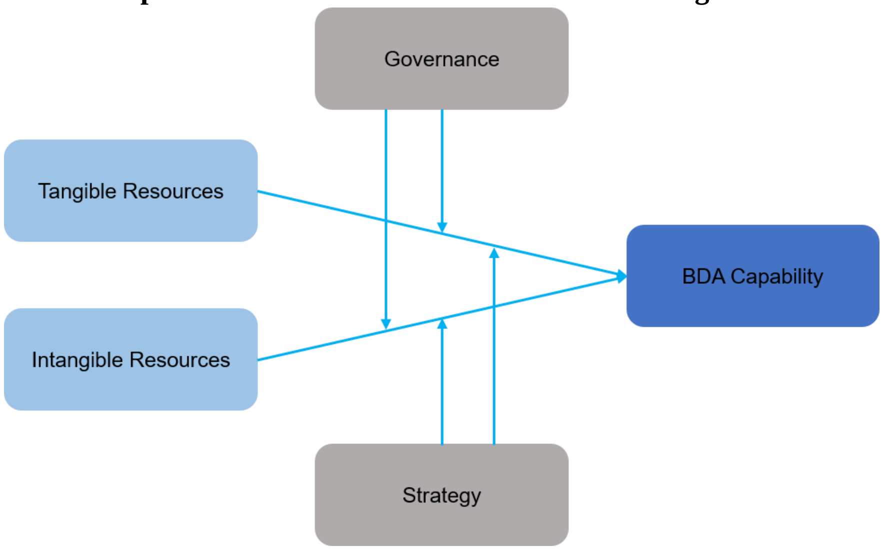

FIGURE 3
Hierarchical Representation of the Final BDAC Assessment Framework for SMEs

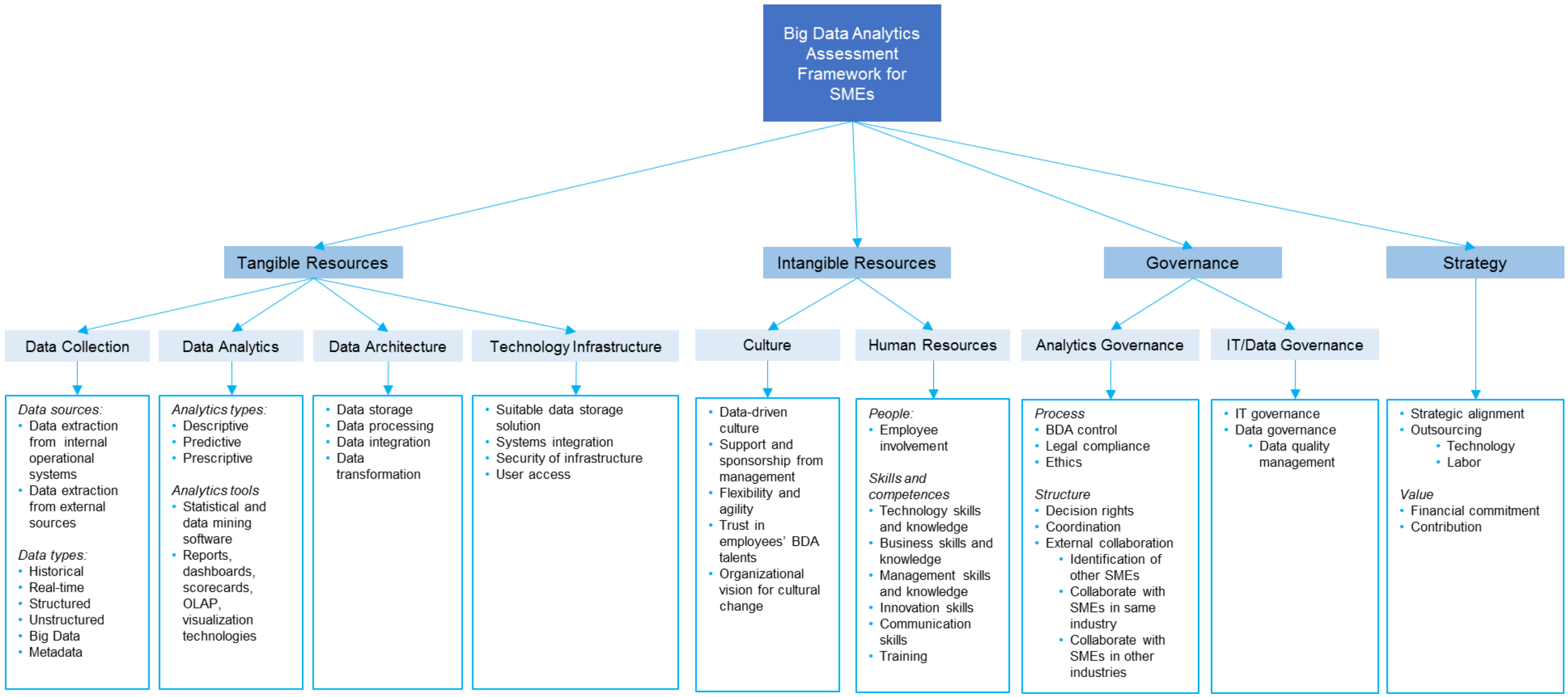

TABLE 1
Interviews for Evaluation of the Preliminary Model

	Job Title	Job Description	Gender
1	Data Analyst	Data analyst of a company with offline as well as online business.	Male
2	Chief Technology and Innovation Officer	CT&I officer at a data science and smart services campus	Male
3	Entrepreneur	Founder and owner of a technology startup providing products for SMEs	Male
4	Product and R&D Manager	Manager at a consultancy firm for BA database technologies.	Female
5	VP Engineering	Engineer of visualization tools and analytics.	Male
6	Associate Professor	Professor of Management with a focus on SMEs.	Male
7	Assistant Professor	Professor of Quantitative Economics with expertise in information systems.	Male
8	Associate Professor	Professor of Strategic Marketing and Innovation Management.	Male

TABLE 2
Interviews Responses for Tangible Resources

Interviewee	1	2	3	4	5	6	7	8
Tangible Resources								
Data extraction from internal operational systems	Yes	Yes	Yes	Yes		Yes	Yes	Yes
Data extraction from external sources	Yes	Yes	Yes	Yes		Yes	Yes	Yes
Historical				Yes			Yes	
Real-time	Yes	Yes		Yes		Yes	Yes	
Structured	Yes			Yes	Yes	Yes	Yes	
Unstructured	Yes			Yes	Yes		Yes	
Big data	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes
Metadata	Yes	Yes	Yes	Yes	Yes		Yes	
Descriptive	Yes	Yes	Yes	Yes	Yes		Yes	
Predictive	No	Yes	Yes	Yes	Yes	Yes	Yes	
Prescriptive	No	No	Yes	Yes	Yes		Yes	
Statistical and data mining software	No		Yes		Yes	Yes		
Reports, dashboards, scorecards, OLAP, visualization technologies	Yes		Yes	Yes	Yes	Yes		
Data storage	Yes		Yes	Yes	Yes	Yes		
Data processing	Yes	No	Yes		Yes	Yes		
Data integration	Yes	No	Yes	Yes	Yes	Yes		
Data transformation	Yes	No	Yes		Yes			
Relationship between the data structure and analytics tools	Yes	No						
Central data warehouse	Yes	No	No	Yes	Yes			
Systems integration	Yes	No	Yes	Yes	Yes	Yes		
Security of infrastructure			Yes	Yes	Yes		Yes	
User access	Yes	No		Yes				

TABLE 3
Interviews Responses for Intangible Resources

Interviewee	1	2	3	4	5	6	7	8
Intangible Resources								
Data-driven culture	Yes	Yes	No		Yes	Yes	Yes	Yes
Leadership support for BA	Yes	Yes	Yes		Yes	Yes	Yes	Yes
Flexibility and agility	Yes		Yes		Yes	Yes		
Trust in employees' BDA talents	Yes	Yes			Yes	Yes	Yes	
Organizational vision for cultural change		Yes	Yes	Yes		Yes	Yes	
Employee involvement	Yes	Yes				Yes		Yes
Technology skills and knowledge	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Business skills and knowledge	Yes	Yes	Yes		Yes		Yes	
Management skills and knowledge	No	Yes	Yes	Yes	Yes		Yes	
Innovation Skills	Yes	Yes	Yes		Yes		Yes	
Communication Skills	Yes	Yes	Yes	Yes	Yes		Yes	Yes
Training	Yes	Yes	Yes		Yes			No

TABLE 4
Interviews Responses for Governance

Interviewee	1	2	3	4	5	6	7	8
Governance								
BDA control		Yes	Yes		Yes		Yes	
Legal compliance		Yes	Yes		Yes	Yes	Yes	Yes
Decision rights	Yes	Yes	Yes		Yes			
Coordination	Yes		Yes		Yes			Yes
IT governance			Yes		Yes		Yes	
Data governance	Yes		Yes		Yes		Yes	

TABLE 5
Interviews Responses for Strategy

Interviewee	1	2	3	4	5	6	7	8
Strategy								
Sponsorship of top management team	Yes	Yes		Yes	Yes	Yes	Yes	Yes
Planning		No			Yes			Yes/No
Change management			Yes			Yes		
Organizational alignment	Yes	No	Yes	Yes		Yes	Yes	
IT strategy alignment	Yes	No					Yes	
Financial commitment								Yes
Risks							Yes	
Contribution	Yes	Yes	Yes	Yes	Yes		Yes	

TABLE 6
Interviews Responses for Additional Dimensions

Interviewee	1	2	3	4	5	6	7	8
Additional Dimensions								
Outsourcing	Yes	Yes	Yes			Yes	Yes	
Data quality management		Yes	Yes					
Ethics		Yes						Yes
External collaboration		Yes	Yes			Yes	Yes	Yes