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How Data Analytics Competencies Can Foster Business Value– A Systematic Review and Way Forward

Sven Klee[a], Andreas Janson[b], and Jan Marco Leimeister[a,b]

[a]Research Center for Information System Design (ITeG), Chair for Information Systems and Interdisciplinary Research Center for IS Design (Iteg), University of Kassel, Kassel, , Germany; [b]Research Center for Information System Design (ITeG), Institute of Information Management (IWI-HSG), University of St. Gallen, St. Gallen, Switzerland

ABSTRACT
Several authors have illustrated the benefits of data in organizations. For realizing benefits, we see two major challenges for organizations. First, there are necessary investments, which have to be justified. Second, adequate data analytics competencies can be seen as enablers for realizing benefits. We aim to support organizations by showing relevant competencies and achievable business values. We present theoretical propositions and a research agenda on how to move the field of data analytics competencies forward.

KEYWORDS
Data analytics; data analytics competency; business value creation

Introduction

"So what's getting ubiquitous and cheap? Data. And what is complementary to data? Analysis" (Varian, 2008). Organizations have realized that data are not a side product but a way to future competitive advantage (Dremel et al., 2017). Several studies demonstrate the relationship between competitive position and the management of information (Chae et al., 2014; Chen et al., 2012; Olszak & Zurada, 2019). Organizations own huge treasure chests of data, but realizing competitive advantage presupposes the organizational use of these data treasure chests (Weibl & Hess, 2019). Building upon this, we see two major challenges for using data and generating competitive advantage. First of all, organizations are confronted with necessary investments in organizational data analytics activities. Investments in information systems can lead to organizational growth and performance (Bharadwaj et al., 1999; Oh & Pinsonneault, 2007). Research has already proven a significant relationship between organizations' operating characteristics and derived benefits by using information systems (Ragowsky et al., 2000). In this context, it is necessary to measure business value but also to pay attention to the multifarious nature of the business value of information technology (Maoz et al., 2007). Economic value, for example, can be measured by an organization's profit increase or business growth, while social value can be measured by employee growth or customer surplus (Günther et al., 2017). To realize these values and further them, it is necessary to analyze data in the operative daily work processes of organizations. The separated data sources are not the starting point for business values, but the synthesized data by gathering completely new insights for decision-making are (Shollo & Galliers, 2016).

At this point, we see the second major challenge for realizing a competitive advantage with the help of data. Organizations rely on systematic data analytics competencies on different organizational levels to analyze the previously mentioned treasure chests (Schüritz et al., 2017). In this context, adequate competencies to use data appropriately can be seen as another important investment, regardless of whether existing competencies are expanded or whether they are supplemented externally. Making strategic data-relevant decisions, deciding whether inductive or deductive procedures are suitable in different situations, or realizing the important data synergies requires respective competencies (Liberatore & Luo, 2013; Persaud, 2020; Shuradze & Wagner, 2016). With our research, we build on these two challenges by showing the effects of data analytics competencies on business value. Thus, it is necessary to explain possible business values in a precise and comprehensible way for organizations. Additionally, we analyze respective data analytics competencies to realize these business values in organizations. Woodruffe (1993) defined competency as a set of behavior patterns that enable people to fulfill tasks and functions. The focus of our research is on such individual employee competencies concerning the fact that there are employees on all organizational levels who are responsible for several analytical tasks. Thus, we

CONTACT Andreas Janson andreas.janson@unisg.ch University of St.Gallen.

consider employees in organizations as a starting point for daily and operative analytical work, which is the foundation for using data and generating business value. While several authors have already researched business values with the help of data in general (Günther et al., 2017; Loebbecke & Picot, 2015; Shollo & Galliers, 2016) and also many authors have analyzed data analytics competencies from a business and education perspective (Cech et al., 2018; Cegielski & Jones-Farmer, 2016; Costa et al., 2017), we want to close a research gap by combining data analytics competency and business value by presenting it in a practical and comprehensive way for organizations. This leads us to the following research question (RQ) for our paper:

RQ: How can data analytics competencies support the development of business value?

To answer the RQ stated above, in the following section we provide a brief overview of the conceptual background concerning competencies and previous work that relates to data competency, as well as of concepts of business value. In the third section, we present our methodological overview following Vom Brocke et al. (2015) in order to gain insights about data competencies in prior literature, and how we complemented those theory-based insights through interviews following Bogner et al. (2014). In the fourth section, we present our findings concerning relevant data analytics competencies and we scaffold these findings with the concept for realizing value out of big data from Günther et al. (2017). In this context, we aim to develop theoretical propositions for deriving business value with the help of data analytics competencies. Building on this, we discuss our results by determining theoretical and practical implications as well as limitations of our research. In the last section, we summarize the results, and we give a short outlook on the next steps.

Conceptual background

In this section, we present our conceptual background by clarifying the terms of data analytics for our purposes, including a short overview of different competency frameworks as a foundation. Furthermore, we define the term competencies in the area of data analytics for our purposes. Finally, we pay attention to a definition of value in the context of data analytics with regard to the goals of our research.

Data analytics in organizations

As a starting point, we have to make sure that our understanding of data analytics in organizations is clear for the purposes of this paper. There are several definitions of data analytics in relevant publications. Therefore, it is necessary to classify our understanding within these perspectives. First of all, there is an interesting and relevant fact in this context. Only 27% of the companies that invested in data analytics subsequently reported successes through these investments (Colas et al., 2014). Reasons for the high rate of failure were, among others, the data quality, wrong data analytics tools or lack of data analytics competencies (Colas et al., 2014). At this point, two aspects can be determined. First, organizations invest in data analytics and see potential in using data and creating new insights. Second, organizations are not very successful in implementing data analytics. In this context, data analytics in general can be defined as a process of transforming data into actions through analysis and insights in the context of organizational decision-making and problem-solving (Liberatore & Luo, 2013). The more present form within the research of data analytics is Big Data analytics (BDA). BDA is defined as a holistic approach of managing, processing and analyzing the famous 5 V data-related dimensions, characterized by volume, variety, velocity, veracity and value with the purposes of creating actionable insights, delivering sustained value and competitive advantage (Wamba et al., 2017). In the context of our research, we want to avoid a limitation to special forms of data analytics. Although BDA is the most present topic in current research and in the perception of organizations, not all organizations start with BDA. From our perspective, each form of data analytics presupposes investments, for example, for analytics tools, and also requires data analytics competencies. Thus, for our research, we summarize all business-relevant analytical activities as data analytics within this paper.

Competencies in the context of data analytics

Building up on our understanding of data analytics, it is important to define the necessary key aspects of competencies and to clarify eventual associations for our purposes in this paper. Among competency as the central term of this paper, there are numerous other terms and concepts, for example, skills, abilities, capabilities, or data literacy. Data literacy is part of many papers or other works and a ubiquitous term in the field of data (Dunlap & Piro, 2016; Koltay, 2016; Wolff et al., 2016) and is oftentimes described as a set of abilities around the use of data (Wolff et al., 2016). While this definition is limited to the use of data, Schüller et al. (2019) include aspects like attitudes and values, and knowledge and skills. Connected with data literacy, we also have to acknowledge competency as a central term. However, there is a necessity to discuss the difference between the terms competency and competence due to the fact that authors often use them as synonyms. Woodruffe (1993) defined competency as a set of behavior patterns that enable people to fulfill tasks and functions. Kurz and Bartram (2008) described competencies as behavioral repertoires, while competence is a state of achievement, which leads to the fact that competence is primarily backward-looking. With regard to this and to emphasize the forward-looking character, we decided to use the term competency for all aspects of analysis within this paper. Building on that the focus of this paper is on special data analytics competencies, which can be characterized as a set of information technology, domain, and communication competencies (Chen et al., 2012). Within these more generally defined competencies, there are specific forms, which we want to extract out of relevant literature and expert interviews and bring together with the resulting business value with the help of operative work with data in organizations.

Several authors already presented approaches of structuring data analytics competencies by taking different perspectives. Table 1 summarizes example approaches to illustrate the variety of perspectives in terms of content. Obviously, these research papers are only examples and could be supplemented with further ones. We deliberately chose these to show the variety of doing research in the field of data analytics competencies. For our research, we consciously forego a content-related restriction in order to extract all relevant data analytics competencies. Thus, we include all research perspectives in our systematic literature review. Finally, we want to build on existing research efforts by expanding data analytics competencies with resulting effects on business value. Therefore, it is not necessary to relate to specific perspectives. In fact, it is conducive to achieve an added value for organizations by presenting effects on business value by building up data analytics competencies. Thus, the supplement of our approach can be characterized by a practice-oriented perspective with the purpose of presenting an overview for managers in organizations. We aim to support these managers by deriving relevant data analytics competencies from literature and expert knowledge, on the one hand, to create an overview and, on the other hand, to enable a competency gap analysis.

The definition of value in the context of data analytics

The measurement of business value is a central aspect of data analytics. Decision-makers in established organizations are willing to create data-driven organizational change but are confronted with long-standing processes and business models that have ensured the success for decades (Gust et al., 2017). Therefore, justification is needed for changes to foster data analytics in companies. Hence, this raises the question of how business value can be defined or characterized in a useful manner. One general approach is the so-called resource-based view, which argues that the configuration of resources and dynamic capabilities are the two central factors of creating business value (Olszak, 2016). In this context, the acquiring, configuration, reconfiguration and developing of available resources are the key activities of creating business value (Wade & Hulland, 2004). With regard to data value, Ghoshal et al. (2014) stated that benefits depend on the strategic goals of organizations. Social benefits can result from employee growth, productivity or consumer surplus (Loebbecke & Picot, 2015). In this context, Maoz et al. (2007) argued another perspective by separating attained business value of IT (ABVIT) and sustained business value of IT (SBVIT). While the first perspective defines the short-term business value under 2 years, the second one includes long-term considerations (Maoz et al., 2007). However, increasing profit or business growth are examples for economic value with the help of data analytics (Davenport, 2006). Building on this, Akhtar et al. (2019) presented an approach with a resource-based view on Big Data, which they compared to the general resource-based view. Thus, the focus is not on time horizons but on different characteristics of organizational actions to create value. Another approach describes the value of synergy between data, which means that the value of combined data is higher than the value of separated data. Weibl & Hess (2020) argued in their study that the combination of two heterogeneous data sets enhances the informativeness of each data set. At this point, it becomes evident that the value of combining data lies is new insights and patterns for business.

The previously discussed approaches are only a selection and could be supplemented with many more. The foregoing examples also show the complexity of defining and measuring business value. Günther et al. (2017) meet this complexity with an approach that considers different levels within organizations. This multilevel perspective is an adequate starting point for our research; hence, we focus on operative and daily work with data on the one hand but support the presentation of data-relevant complexity within organizations on the other hand. Figure 1 presents three different organizational levels based on the research of Günther et al. (2017).

Table 1.

Authors	Approach of Structuring Data Analytics Competencies
Shirani (2016)	• Focus on industry needs with regard to data analytics competency • Taxonomy of data analytics competenciesFoundation competencies • Introduction to intermediate competencies • Advanced competencies
Ghasemaghaei et al. (2018)	• Focus on effects of data analytics competencies on decision-making • Measuring effects quantitatively with the following results:Data quality competency, bigness of data, analytical competency, domain knowledge and tools sophistication as data analytics competency set • All competencies, except bigness of data, increase decision quality and efficiency
Shankararaman and Gottipati (2016)	• Mapping competencies from the curriculum to industry needs with the help of SFIA Framework • Using LinkedIn profiles for experimental designResults can support students to plan their future paths • The effective use of networks can support students
Debortoli et al. (2014)	• Focus on job advertisements in the areas of business intelligence and Big Data • Business intelligence and Big Data competency taxonomies as final resultSeveral similarities, for example, software engineering or database competency • Business knowledge and technical competency are the most important competencies
*song, I.-Z.; Zhu, Y (2016)	• Focus on necessary education contents for students to build up data analytics competency • Result is a recommendation for education programsThe recommendation includes nine steps • Teaching Chief Data Officer (CDO) contents or following the eight-step data analytics lifecycle model are two examples
Our Research as a delimitation and supplement	• Focus on data analytics competencies in organizations to fulfill operational analytical activities for creating business value • Result is a practice-oriented overview of relevant data analytics competencies for employees in organizations Includes three main categories for a better understanding • Within these categories, further subcategories summarize relevant data analytics competencies aimed to inform responsible managers in organizations about the scope of relevant competencies and eventually existing lack of data analytics competencies within their organizations

Work-practice level

The work-practice level summarizes operative tasks within organizations. Therefore, it describes the daily work with data and generating business value in daily processes. Within this level, Günther et al. (2017) extracted the key debates around inductive and deductive BDA as well as algorithmic and human-based intelligence out of the relevant literature. With regard to our research, this work-practice level is the most relevant one due to the fact that it focuses on the operative work. Individual data analytics competencies of employees directly support this operative work.

Organizational level

The next level is the organizational level, which describes the generating of business value by creating a holistic data-oriented organizational model. Günther et al. (2017) also extracted two debates. The first one is about centralized or decentralized data analytics capabilities, and the second one focuses on the improvement of existing business models, the complete innovation of business models or hybrid forms. Thus, the organizational level is the subordinated sum of operative aspects and focuses on aggregated organizational decisions.

Supra-organizational level

Building up on this, the supra-organizational level also includes external data. Thus, debates on topics beyond organizational boundaries are the key focus. In this context, shareholders, governments, research institutes or customers are exemplary actors (Günther et al., 2017). Therefore, one debate is about controlled or open access to data. At this point, it becomes evident that all previously mentioned actors and many more have to be considered, which leads to the high complexity of decision-making. Another debate builds on that by considering the balance between neglecting or minimizing the social risks of data value realization (Günther et al., 2017). It is obvious that much data that are informative and valuable can also be highly personal and vulnerable.

For our further consideration, we use the level classification of Günther et al. (2017) as a starting point due to the fact that it shows the different specifications of data-relevant actors and structures in organizations. In this context, we can directly point out our goal of analyzing individual data analytics competencies of employees in their operative and daily work processes. Thus, we directly build on the work-practice level and leave our discussions about the other two levels short with regard to possible future research.

Methodology

In the following section, we present the methodological procedure. First, we explain our conducted systematic literature review in detail. Subsequently, we give an overview of the first conducted expert interviews by presenting key facts about the procedures, interviewees, and the content.

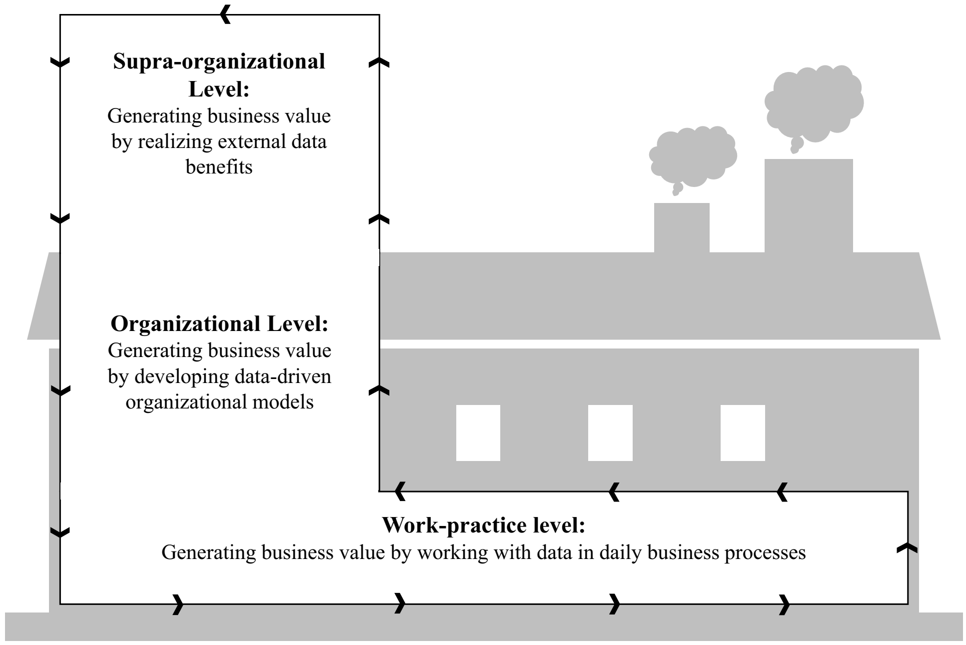

Figure 1.

Systematic literature review

To reach our goal of creating a framework of relevant data competencies, we conducted a systematic literature review that follows the guidelines of Vom Brocke et al. (2015). The first step describes the definition of an appropriate search string. This search string is the result of test searches in common databases and includes terms in the fields of data analytics and competencies. To build on that, more detailed "data analytics" or "business analytics" represent common terms in the current research. The combination with different terms of "competency" completed the proceeded search string. As described before, "competence" is often used as a synonym, which led us to add both terms to reach a thorough overview. Test searches also lead to terms like "skill," "ability," "capability," "literacy" or "knowledge".

We also added "education" to include papers that focus on teaching analytics competencies. In a second step, we decided to choose the seven databases ACM Digital Library, Electronic Library of the Association for Information Systems (AISeL), EBSCO (Business Source Premier), Emerald, IEEE Xplore, JSTOR and ScienceDirect because of the most auspicious search results. The third step was the final provision of the literature review. In the period between April 1, 2020, and April 10, 2020, the presented search string was applied in the seven chosen databases. Books were excluded from all databases because of the very dynamic research field and peer-reviewed papers were chosen if possible. Keyword and title searches led to 112 initial results. The last step was a more detailed screening by using abstract and full-text analysis. Finally, we arrived at 38 relevant papers. With the help of a backward search, two more papers increased the result to 40 papers. With the help of a forward search after the first review, we could add three more papers. In summary, there are 43 papers that are the core content of this paper. Figure 2 presents the steps and the final results. We also marked the analyzed papers of our systematic literature review with an asterisk in the references.

Conducted interviews to complement structured literature review

We conducted the first six interviews according to Bogner et al. (2014) with eight interviewees in a period of 5 weeks. The interviews were partly on-site and partly by telephone. All interviews were recorded and fully transcribed. We designed all interviews in a structured way to direct the conversation to relevant data analytics competencies. The eight interviewed experts work in five different organizations. Table 2 summarizes key facts about the interviews, the experts and their organizations. We included the manufacturing industry, as well as auditing companies and public authorities. The companies operate internationally. All organizations have more than 2000 employees. The internal focus was on IT backgrounds to make sure that the experts have professional touchpoints with data analytics competencies within their daily work environment.

Within the interviews, there were several content foci. For the purposes of relevant data analytics competencies and how they relate to business value, we asked the experts about:

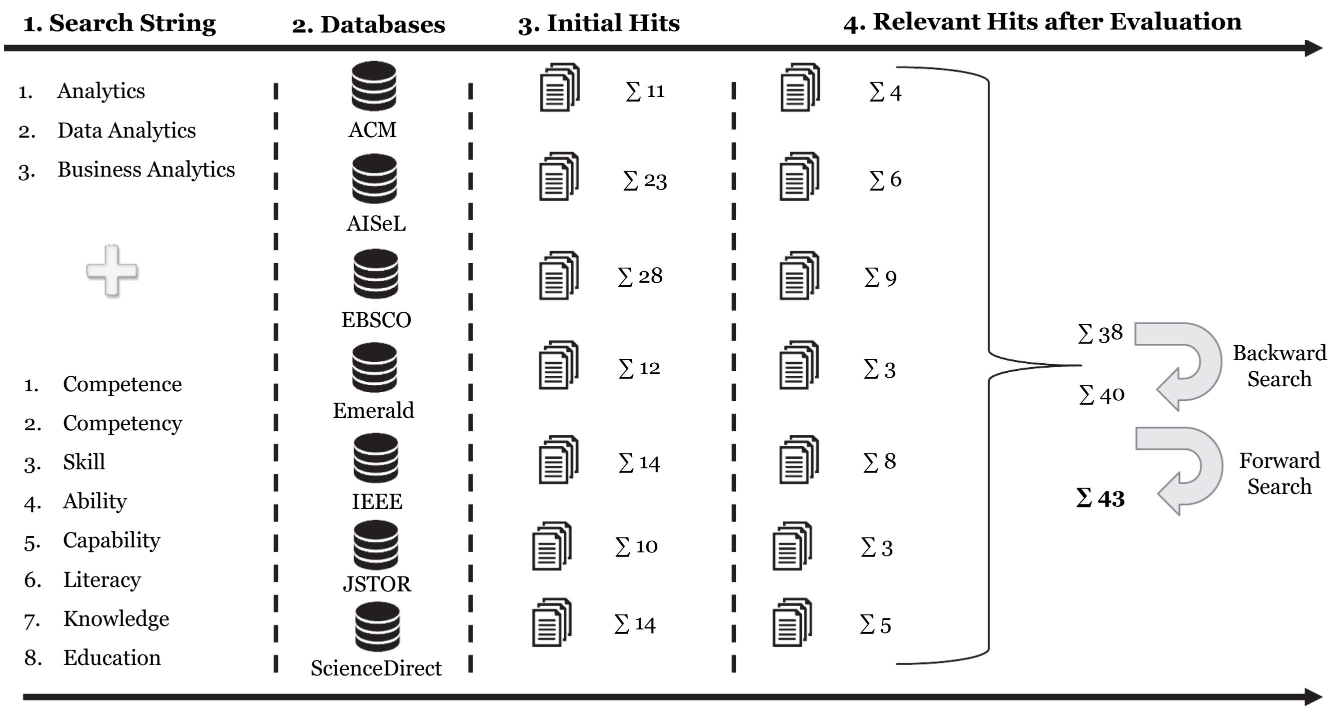

Figure 2.

(1) data analytics in their organizations in general and building on that,

(2) relevant experiences with it and, finally,

(3) specific data analytics competencies and the expert's assessment on them.

We introduced already analyzed competencies out of the relevant literature and discussed further ones from the expert's experience. As a result, we extracted the information and put them together with the data analytics competencies out of the literature. The conducted structured interviews supplement the literature review and helped to extend the theory-based findings with practical assessments and also new insights. The mixture of different organizations and public authorities enabled a broad coverage of experiences.

Table 3 summarizes the extracted data analytics competencies out of the systematic literature review and the expert interviews including exemplary sources. Obviously, many extracted data analytics competencies were part of several papers or interviews. Competency in the area of data laws, guidelines, norms and standards, for example, was part of nearly all sources. To make sense out of the extracted competencies, we now aggregate those findings and provide a theoretical sensemaking of the findings in the next sections.

Table 2.

No.	Industry	Interviewee	Employed Since	Time
1	Auditing Company	System Developer	2014	51:05
2	Manufacturing Industry (Hygiene Products)	IT Project Manager	2012	01:05:28
3	Manufacturing Industry (Hygiene Products)	IT Project Manager	2018	
4	Public Authority	IT Project Manager	2019	59:00
5	Auditing Company	System Developer	2016	01:04:05
6	Public Authority	IT Project Manager	2017	59:54
7	Public Authority	IT Project Manager	2016	
8	Auditing Company	Higher Management	2011	32:25

Findings and propositions for future research

In this section, we discuss the results of the systematic literature review and the conducted interviews. First of all, we explain the extracted data analytics competencies. Building on that, we analyze how these data analytics competencies can foster business value in organizations.

Data analytics competencies framework

In sum, we could extract 34 different data analytics competencies within the relevant papers and expert interviews. Obviously, these competencies are connected to each other. Thus, we decided to use a structure for creating a better understanding and a comprehensible overview. Based on the amount of extracted data

Table 3.

Data Analytics Competencies	Exemplary Source	Data Analytics Competencies	Exemplary Source
1. Balancing benefits and costs	Schüritz et al. (2017)	18. OLAP	Chiang et al. (2012)
2. Business design	Mitri and S. (2015)	19. PHP/JavaScript	Debortoli et al. (2014)
3. Combination of existing and new analytic methods, tools and technology	Interviewee 4	20. Preparing analytic results for customer	Interviewee 2
4. Communicate and visualize new insights in a suitable way for management	Interviewee 8; Calzada Prado & Marzal (2013)	21. Preparing insights for strategic decision-making	Interviewee 8
5. Connecting methods and customer demands	Interviewee 1	22. Process modeling	Interviewee 5
6. Data-relevant laws, guidelines, norms and standards	*Topi, H.; Markus, L (2015)	23. Process/Text/Web mining	Chen et al. (2012)
7. Descriptive measures	Mitri and S. (2015)	24. PYTHON	Altmann, (2019)
8. ETL	Shuradze and Wagner, (2016)	25. R	Cegielski and Jones-Farmer (2016)
9. Hadoop	*Song, I.-Z.; Zhu, Y (2016)	26. Sampling methods	Mitri and S. (2015)
10. Machine Learning	*Topi, H.; Markus, L (2015)	27. SAS	Cegielski and Jones-Farmer (2016)
11. MapReduce	Marttila-Kontio et al. (2014) Dubey et al. (2019)	28. Scouting new and relevant data sources	Interviewee 1
12. Mobile sensor-based analytics	Chen et al. (2012)	29. Social media analytics	Chen et al. (2012)
13. Multivariate analysis	Cech et al. (2018) Gupta and George, (2016)	30. SPSS	Cegielski and Jones-Farmer (2016)
14. Networking/ interdisciplinary collaboration	Akter et al. (2016)	31. Selection of suitable tools and software	Akter et al. (2016)
15. .NET	Debortoli et al. (2014)	32. Selection of suitable statistical methods	Gorman and Klimberg, (2014)
16. NewSQL	Dinter et al. (2017)	33. Understanding of business processes	Liberatore and Luo, (2013)
17. NoSQL	Miller, (2019)	34. Understanding of relevant KPI	Mikalef, Giannakos, Pappas, et al. (2018)

analytics competencies, we do not discuss all of them in detail. However, we created Table 4 to summarize the results.

First, we created the category "Analytical Domain Competency," which summarizes all competencies focusing on the context of the respective work environment. For example, connecting relevant methods to fulfill customer demands is one specific data analytics competency. It describes the understanding of customer data needs and the selection of the adequate methods to achieve this goal (Cech et al., 2018). For interpreting customer demands, it is necessary to understand the underlying business processes as well (Akter et al., 2016). Understanding business processes is also connected with networking and interdisciplinary collaboration. Hence, there are complex structures with several responsibilities. Only analyzing the relevant data cannot be seen as the final result without an appropriate and customer-oriented preparation of the results (Cech et al., 2018).

In the second category, we summarized all data analytics competencies in the field of data management in general. With regard to the number of relevant competencies, we created subcategories. We also included the more technical database-oriented competencies. This category encompasses the handling of data in the business context. In this context, we extracted, for example, NoSQL (Debortoli et al., 2014; Dinter et al., 2017), Hadoop (*Tambe, P, 2014) or OLAP (Chiang et al., 2012) competencies and summarized them under the subcategory "database management." We also extracted several tools, software and method competencies. Cegielski and Jones-Farmer (2016) presented, for example, SPSS or SAS in their multi-method study. Statistical methods such as multivariate analysis (Gorman & Klimberg, 2014), sampling methods or descriptive measures (Mitri & S., 2015) are self-explanatory on the one hand but also self-evident on the other hand for handling and analyzing data. Concerning this subcategory, we also extracted more overarching competencies. Managing the combination of existing and new methods, for example, describes the definition of effective method portfolios with regard to different demands (Mikalef & Krogstie, 2019). In this context, a balancing of costs and usefulness of analytical activities is another ambitious competency. New sources, tools, methods or software can cause costs and need an equivalent value (Schüritz et al., 2017).

Within the subcategory "Administrative," we summarized data analytics competencies with a more strategic and challenging character. The relevant literature often separates the operative analytical activities and management-oriented decision support. Therefore, we also separated the data

Table 4.

Competency Category	Specific Competencies	
Analytical Domain Competency	• Connecting methods and customer demands • Preparing analytic results for customer • Understanding of business processes	• Understanding of relevant KPI • Business design • Process modeling • Networking/interdisciplinary collaboration
Data Management Competency	• Tool/software/method management o Combination of existing and new analytic methods, tools and technology o Selection of suitable tools and software o Selection of suitable statistical methods o Balancing benefits and costs o Multivariate analysis o Sampling methods o Descriptive measures o SPSS o SAS o Scouting new and relevant data sources	• Administrative o Preparing insights for strategic decision-making o Communicate and visualize new insights in a suitable way for management o Data-relevant laws, guidelines, norms and standards • Database management o NewSQL o NoSQL o Hadoop o MapReduce o OLAP o ETL
Technical/ Technological Data Competency	• Programming languages o .NET o PHP/JavaScript o R o PYTHON	• Technology o Machine learning o Social media analytics o Mobile sensor-based analytics o Process/text/web mining

preparation for management from the previously explained data preparation in the context of domain competency. It describes the direct support of the management for strategic decision-making (Mitri & S., 2015). This also includes the adequate visualization for the management, which assumes further competencies in comparison to experienced analytical activities in daily business routines (Prifti et al., 2017). Another very specific competency in the category focuses on data-relevant laws, guidelines, norms or standards (Dinter et al., 2017; Grillenberger & Romeike, 2018; Mikalef, Giannakos, Pappas, et al., 2018), such as the General Data Protection Regulation (GDPR) in the European Union or further national and international regulations or recommendations. It is not a surprise that authors also pay attention to laws and further regulations for handling data in organizations. Hence, the recent scandals directed the attention of all stakeholders to these topics (Dickhaut et al., 2021).

Finally, we created the category "Technical and Technological Data Competency" and, within, the two subcategories "Programming languages" and "Technology." While the programming languages are well known and mainly familiar, the extracted competencies with regard to technologies have an interesting side effect. It becomes evident that these competencies are, more than others, subject to permanent innovation. Thus, organizations have to permanently pay attention to developments and their employee's competencies. Mobile- and sensor-based content are one important reason for previously mentioned treasure chests of data (Chen et al., 2012). This development goes hand in hand with the development of the "Internet of Things" (IoT). Of course, this development will go on and, as a result, the necessary data analytic competencies are subject to a continuous process of change.

With the chosen categories and related subcategories, we intended to create a comprehensive overview. Many further visualizations are possible. We do not claim completeness and it is self-explanatory that there are overlapping data analytics competencies when Table 2 is considered without the context. That is why we emphasize the further use of it within the next steps of our research.

Data analytics competencies as a prerequisite for business value

In this section, we define and explain our propositions with regard to business value with the help of data analytics competencies. The goal is to analyze how our extracted data analytics competencies can foster business value. As previously mentioned, we use the concept of Günther et al. (2017). Their propositions of business value refer to the intersections of the three presented levels. Within this concept, we pick up the work-

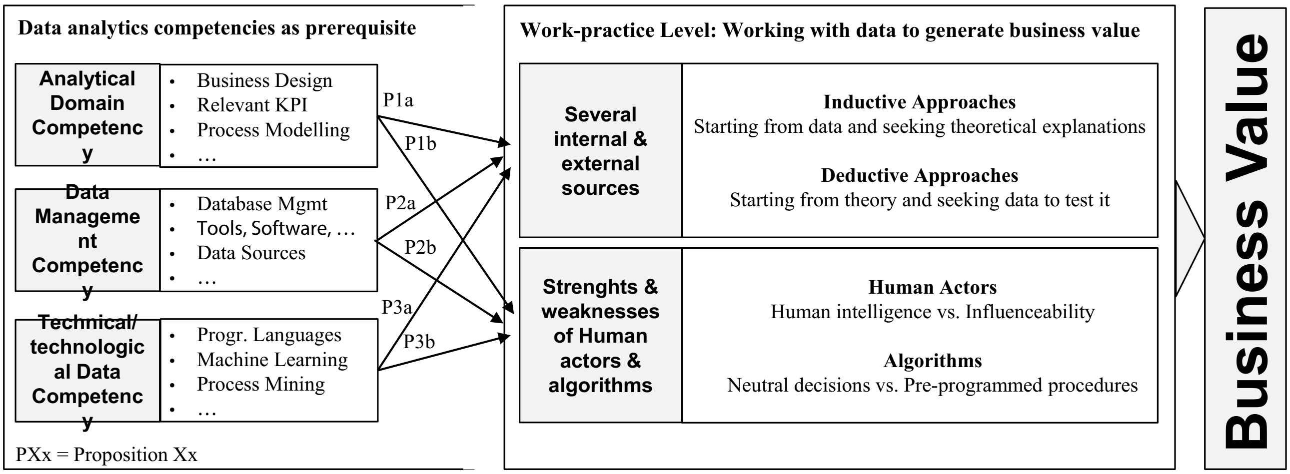

Figure 3.

practice level, which describes the daily work with data. This is a suitable starting point for our extracted data analytics competencies. This work-practice level outlines the debates about internal and external sources and the stress ratio between strengths and weaknesses of human actors and algorithms (Günther et al., 2017). Figure 3 represents the extracted data analytics competencies and the work-practice level, connected with six propositions, which we present in detail in the following section. We propose the potential of increasing business value by building up these data analytics competencies and present the possible effects on the two debates according to Günther et al. (2017) and the underlying aspects.

First, domain competency summarizes all aspects of daily work environments with regard to analytical activities. Therefore, we created two propositions for generating business value:

(1) Proposition 1a: A high level of analytical domain competency creates business value by improving inductive and deductive analytical work.
(2) Proposition 1b: A high level of analytical domain competency creates business value by relativizing the stress ratio between human actors and algorithms.

First, we propose that a high level of analytical domain competency creates business value by improving inductive and deductive analytical work. Starting from a set of data and analyzing this set to gain insights is the inductive way of data analysis, whereas the theoretical part and, subsequently, seeking for data is characterized as deductive analysis (Günther et al., 2017). Both approaches have the goal to gain new insights, for example, for decision-making (Günther et al., 2017). At this point, the business value becomes evident but also that a valuation of insights is only possible with knowledge about valuable insights. Although there is an awareness of the value of data, in practice there are still many problems regarding the final use and implementation (Otto, 2015). Therefore, employees need an understanding of business processes or relevant key performance indicators (KPI) (Debortoli et al., 2014). Therefore, we propose that a thorough understanding of underlying business processes leads to a more effective inductive analysis of data.

Hence, there is less coordination between requesters or customers and employees. Furthermore, the analytical work can start with a clear content-related direction without time-consuming meetings. Also, deductive theory building is more effective with distinct knowledge about underlying business processes and competencies regarding business design or process modeling. Building on that, the competence of adequate data preparation reduces efforts. Hence, employees have a better understanding of the relevant business or customer backgrounds.

We further propose that a high level of domain analytical competency creates business value by relativizing the stress ratio between human actors and algorithms. Where human actors can contribute their human intelligence with regard to analytical activities, an influenceability is often put forward (Günther et al., 2017). Vice versa, algorithms make neutral decisions but follow pre-programmed procedures without regarding influencing factors, such as necessary personal rights or further sensitive aspects (Günther et al., 2017). Obviously, organizations rely on their employees to do analytical work for fostering business value, as well as algorithms with regard to increasing amounts of data. Thus, the mentioned stress ratio is an important field of interest. Building up on this, we propose that a distinct analytical domain competency enables adequate weighting. If employees have deep knowledge of underlying business processes, relevant KPI, the requesting customers and further issues, they are able to make reasonable decisions in the interests of customers. With regard to this, customer's acceptance toward analytical results increases. In this context, interdisciplinary collaboration and associated networking activities can reduce the mistrust of customers. Vice versa, employees can explain the functionalities of used algorithms to customers. Grublješič and Jaklič (2015) argued that individual actors in organizations can influence the acceptance of information technology by describing a case in which one project manager leaving led to a decrease in the use of a business intelligence system. Thus, individual employees can have a decisive impact on a customer's acceptance.

Our second category summarizes data management competencies in general. In this context, we propose the following effects and resulting business value:

(1) Proposition 2a: A high level of data management competency creates business value by structuring the sources and analytical activities.
(2) Proposition 2b: A high level of data management competency creates business value by setting a frame for balancing strengths and weaknesses of human actors and algorithms.

As previously mentioned, inductive as well as deductive analytical work has the goal of gaining new insights and thus creating business value with it. We already explained the effects of domain competency. These effects relate to sideline activities of analytical work, such as underlying business processes, KPIs or customer aspects. Data management competency, however, refers to detailed and data-oriented structuration. Thus, we talk about practical data analytics itself. Regardless of whether inductive or deductive approaches are chosen, there is a necessity to apply the adequate tools, further software and several methods. SPSS or SAS are established software examples for doing valuable analytical work (Cegielski & Jones-Farmer, 2016). Several statistical methods, such as multivariate analysis, sampling methods or descriptive measures are basic requirements for analytical work (Gorman & Klimberg, 2014; Mitri & S., 2015). Therefore, these data analytics competencies can be seen as a prerequisite for the analytical work-practice in organizations. Thus, business value relies on employees with these respective competencies. Building on that, the more holistic competency to combine these tools, software or methods can ensure further business value. For a suitable selection, the responsible employees must be able to balance the costs and benefits of these tools, software and methods (Schüritz et al., 2017).

With regard to analytical activities in organizations, the database management itself can also be seen as a central prerequisite for generating value. We extracted several competencies, such as New SQL, NoSQL, Hadoop or MapReduce (Marttila-Kontio et al., 2014; Miller, 2019; Shuradze & Wagner, 2016). In this context, the efficient database management ensures all further analytical work and moreover the resulting business values. Following the debates of Günther et al. (2017), the inductive or deductive approaches are ideal from a theoretical perspective, whereas the practical reality often lead to boundaries with regard to personal mind-sets or interpretations. We propose that distinctive competencies of preparing, visualizing and communicating can reduce such boundaries and increase business value as a result. At this point, the difference to previously mentioned customer-oriented and very operative data preparation competencies becomes evident. While the first one addresses operative work task fulfilling, the preparation for management is directly related to strategic decision-making and problem solving (Janson et al., 2020). From our point of view, this also includes higher complexity and justification requirements for what efficient data management is necessary. Therefore, we separated the daily operative data preparation from the management-oriented one. All of this points to the fact that highly pronounced data management competencies can address the structuration of sources and analytical activities in organizations. Therefore, our arguments directly take up the aspects of the work-practice level according to Günther et al. (2017). We also stated that some data analytics competencies can be seen as prerequisites for creating business value.

We further propose increasing the business value by setting a frame for strengths and weaknesses of human actors and algorithms. Günther et al. (2017) argued that human intelligence is one major advantage with regard to data analytics, whereas influence-ability can lead to serious consequences for further business value. In contrast to that, algorithms are neutral but follow pre-programmed procedures without the ability to weigh issues, whereby the business value can also decrease (Günther et al., 2017). In this context, we propose that data management competencies ensure business value through employees' conscious judgment of issues. Employees with distinct tool, software or method competencies can evaluate data or subordinated results in a more effective way. Building on that, there is a deeper understanding of algorithm functionalities. This can lead to a pronounced awareness of algorithm boundaries on the one hand and to a better understanding of algorithms for all data requesters by imparting knowledge on the other hand.

Thus, the correct and effective interpretation and use of data, finally, improves business value. Employees can further use their data competencies while preparing, communicating and visualizing data results for management. Possible interpretation errors or predominant mistrust can be reduced if employees are able to impart data results adequately, which can increase the business value of data analytics. Finally, the debates in the area of data analytics often include issues like data privacy or security. Especially if algorithms are used and the previously explained human intelligence is missing, competencies about laws, guidelines, norms and standards are essential. Obviously, this can ensure the correctness of organizational data analytics, which is directly connected to better business value. Additionally, in this context, the trust of requesters like managers from all levels can be increased. Therefore, the acceptance and the use of new insights can be fostered.

Our third category summarizes all extracted technical data analytics competencies. Our findings include relevant programming languages and current technologies with high value for analytical activities. Like before, we also create two propositions for creating business value with these technical data competencies:

(1) Proposition 3a: A high level of technical and technological data competency creates business value by improving in-depth analytical activities.
(2) Proposition 3b: A high level of technical and technological data competency creates business value by fostering the technical and technological principles.

Within the relevant literature, the authors discussed established programming languages like R, .NET or PYTHON (Altmann, 2019; Debortoli et al., 2014: Shuradze & Wagner, 2016). We propose that programming competency improves the business value while doing inductive or deductive analytics. Obviously, there are several tools or extensive software offers that are also usable for employees without distinct statistical or programming competencies. The potential of analytical activities, whether inductive or deductive, is limited to the functionalities of such tools and software. In contrast to this, employees with pronounced competencies of programming languages can create individual and case-specific solutions to realize entire potentials. As a result, there is a positive impact on business value. We also propose further potentials by combining existing tools or software and programming competencies of employees. Building on this, technological competencies can support these potentials. Olszak, (2016) pointed out in her study about an understanding of business intelligence that the use of appropriate technologies is, among other things, a prerequisite for realizing benefits. The data sources are the foundation of analytical activities, whether they are inductive or deductive approaches (Günther et al., 2017). Social media are suppliers for a high volume of data, but it is necessary to analyze this volume in a profitable way with technological competency (Chen et al., 2012). With the help of distinct competencies, such data sources can offer valuable starting points for later inductive and deductive approaches. Directly connected to this, mobile sensor-based analytics, as well as web, process or text mining are comparable ways of creating precious external data sources for analytical work (Chen et al., 2012). In this context, Varanasi and Tanniru (2015) already conducted a text mining study and demonstrated the effectiveness with regard to data-value-generation Balkan and Kholod (2015), for example, illustrated the use of intelligent video analytics for supporting decision-making in organizations.

As a summary, new and valuable insights for creating business value can result from new sources, which substantiates the necessity of technical and technological data competency to realize value. We also extracted machine learning as a relevant competency for data analytics. With a rising industry of artificial intelligence, machine learning competencies offer new ways for data analytics (Costa et al., 2017; Debortoli et al., 2014; Prifti et al., 2017). As a summary, technical and technological data competencies can be seen as an enabler for many steps in the process of data analytics on the one hand and as a starting point for a future-oriented alignment of organizational data analytics on the other hand.

Building upon this, we propose that a high level of technical and technological competencies lead to business value by fostering technical and technological principles. This proposition refers to the stress ratio between human actors and algorithms and the relevant aspects. Especially data in the field of artificial intelligence are often connected to trust issues. Thus, analytical results can meet resistance because of mistrust. Competency in the field can break down mistrust for customers, regardless of whether management or operational departments are the requesters. On the one hand, the quality of analytical work can be ensured. On the other hand, customers trust analytical results if they are informed about the existing competencies. This is based on the employee's knowledge about the functionalities of algorithms, regardless of machine learning or other automated data evaluations. In summary, business value on a work-practice level includes debates about human actors and algorithms (Günther et al., 2017). Technical and technological data competency, however, can be seen as an enabler of this business value. With distinct competencies, employees can also balance the combination with regard to the usefulness of human analytical work or algorithms. Thus, employees can define the degree and content-based directions of algorithms within analytical activities in organizations.

Effects of data analytics competencies on (supra-) organizational level

As previously mentioned, our illustrated propositions for business value with the help of data analytics competencies addressed the daily work with data and is therefore based on the work-practice level of Günther et al. (2017). Nevertheless, we also assume positive effects of pronounced data analytics competencies on the other two levels according to Günther et al. (2017). For creating data capabilities on the organizational level, one important success factor is the combination of skills in multidisciplinary teams (Gao et al., 2015). We also see distinct analytical domain competencies as a success factor for designing adequate data-oriented business models.

With regard to the supra-organizational level of Günther et al. (2017), we assume positive effects with the help of data analytics competencies. First, our extracted data management competencies include the data source control and related issues like balancing costs, benefits and competencies in the field of data laws, guidelines, norms and standards. Especially the last one can also play a decisive role with regard to minimizing and neglecting the social risks of data value realizations, which is an important debate on the supra-organizational level according to Günther et al. (2017). These positive effects have a mainly indirect character. Hence, the organizational and supra-organizational levels are highly aggregated perspectives. Therefore, we prioritized the focus on the work-practice level. Nevertheless, this can be seen as an auspicious outlook for further research.

Discussion and implications

After presenting the findings of our systematic literature review and conducting interviews as well as associated propositions for future research, we discuss the results and implications achieved so far. Therefore, we discuss theoretical and practical implications as well as limitations of our research.

Theoretical implications

From a theoretical perspective, a positive impact of data analytics in general or associated topics on business value in organizations is widely accepted (Akhtar et al., 2019). Building on this, there are several approaches for showing potentials of data analytics in business environments (Akhtar et al., 2019; Gupta & George, 2016; Mikalef & Krogstie, 2020). Furthermore, research has already acquired extensive knowledge about data analytics competency and associated research fields (Debortoli et al., 2014; Shankararaman & Gottipati, 2016; Shirani, 2016). In this context, we see two major values and theoretical contributions of our paper. First, this research adds further insights by bringing together current knowledge about business value with the help of data analytics and detailed data competencies to foster this business value in organizations. In the area of business value, with the help of data analytics, many authors have intensified their research (Akhtar et al., 2019; Akter et al., 2016; Ghasemaghaei et al., 2018). Additionally, there are many rather high-level approaches with regard to organizations' capabilities. Dubey et al. (2019) demonstrated an improved decision-making performance with the help of entrepreneurial orientation. Mikalef et al. (2019a) illustrated the mediating role of dynamic capabilities and showed that non-technical dimensions are essential while implementing and using Big Data in organizations (among other things). In addition to this, Ranjan and Foropon (2020) present the potentials of competitive intelligence within organizations. Ranjan and Foropon (2020) also stated that managers need to build up personnel skills for successfully implementing Big Data in organizations. These three examples represent a very small selection of approaches aimed at exploring the potential of Big Data in organizations. Building on that we supplement the current

Table 5.

Propositions	Exemplary Hypotheses
P1a: A high level of analytical domain competency creates business value by improving inductive and deductive analytical work.	H1a: Employees with a high level of analytical domain competency will achieve better results by transferring analytical requests.
P1b: A high level of analytical domain competency creates business value by relativizing the stress ratio between human actors and algorithms.	H1b: Employees with a high level of analytical domain competency will improve the trust of requesters in analytical results.
P2a: A high level of data management competency creates business value by structuring the sources and analytical activities.	H2a: Employees with a high level of data management competency achieve better results by conducting analytical activities.
P2b: A high level of data management competency creates business value by setting a frame for balancing strengths and weaknesses of human actors and algorithms.	H2b: Employees with a high level of data management competency will improve an efficient weighting of human actors and algorithms by conducting analytical work.
P3a: A high level of technical and technological data competency creates business value by improving in-depth analytical activities.	H3a: Employees with a high level of technical and technological data competency achieve better results by using organization's analytical tools.
P3b: A high level of technical and technological data competency creates business value by fostering technical and technological principles.	H3b: Employees with a high level of technical and technological data competency can foster the application of new technologies, for example, Artificial Intelligence.

body of knowledge by fostering a discussion about necessary investments in data analytics as well as associated justifications from an organizational perspective.

This also leads us to the second major value of our research. With regard to Ranjan and Foropon (2020), there is a high relevance of personnel competencies in the field of data analytics. Therefore, we moved our focus to employees and their data analytics competencies and to possible business value with the help of these competencies. Thus, we take a different perspective by combining two well researched fields, i.e., data analytics competencies and business value, with the help of data analytics and intend to close a research gap in this field. Thus, it is valuable to emphasize data analytics competencies in organizations from our point of view. As a result, our research can complement existing findings, especially through the operationalization of our theoretical model and according hypotheses (see Table 5).

Table 5 connects our propositions with exemplary hypothesis, which are testable in organizations. These hypotheses can be seen as another important step for increasing the understanding of BDA competencies and how they derive value in action.

Practical implications

From a practical perspective, we see a research gap with regard to practice-relevant derivations, which organizations can classify directly and in the best case directly implement in their operational processes. Therefore, we aim to present a precise and detailed approach to data analytics competencies and associated business value that is usable by organizations. The focus was on individual employee competencies, since we see this organizational level as a necessary starting point for organizations. As described before, we see two major challenges for organizations. Firstly, all data analytics activities are connected with investments (Dubey et al., 2020) and have to be justified. Secondly, generating business value with data analytics after arranging investments presupposes adequate competencies within the organization (Ranjan & Foropon, 2020; Wamba et al., 2017). Building on this, our research can be seen as an approach of supporting managers in organizations by facing these challenges. We present an overview of necessary employee competencies and developed categories for a better understanding of the application within organizations. This cannot be seen as a revolutionary approach, which is why there are numerous approaches of individual data analytics competencies in the relevant literature. Mainly, the compilation of existing approaches in a more practically oriented way can be seen as an additional value and a supplement to existing ones. Above all, the combination of these data analytics competencies with the associated business value is the most significant supplement to existing literature. We aimed to support managers in organizations by pointing out achievable business values after investing in data analytics and building up the necessary competencies. Therefore, we outlined possible values with the help of special data analytics competencies by challenging the work-practice level according to Günter et al. (2017).

Limitations

Considering the limitations of our research, we can state that the presented data analytics competencies cannot be regarded as complete. It is a dynamic research field with continuously changing contents and therefore continuously changing data-relevant competencies. New technologies or new legal requirements are two examples for developments and associated changes for necessary competencies. Furthermore, we do not claim completeness regarding the presented propositions of realizing business value. We chose one approach to show the possible values for businesses. There are more perspectives for research and associated debates. We already started an outlook with the help of the (supra-)organizational levels according to Günther et al. (2017). Building on this, our propositions are as dynamic as data analytics competencies are. Such future developments can influence our assumptions and, thus, it will be necessary to observe such changes and incorporate them into the research activities, which can be seen as a limitation for this research. For example, approaches, such as automated machine learning (AutoML; He et al., 2021) are proliferating into business practice with the potential to radically disrupt data science in businesses (Templeton et al., 2019). AutoML reduces the demand for data scientists and at the same time enabling domain experts, i.e., related to creating business value, to automatically build ML applications without strong requirements for knowledge related to ML and statistics (He et al., 2021). Thus, competencies may shift in the future more to the analytical domain competency, compared to the technical competency perspective in our model. Additionally, we should also account for effects on value co-creation that relate to the role of ML platforms and associated ecosystems (Knote et al., 2020).

Furthermore, our propositions have to be validated with advanced research activities. So far, we have used insights from relevant literature and knowledge from eight conducted interviews for our first results. Although we have included public authorities and private organizations, as well as different employee levels, we are aware that our previous activities cannot be seen as encompassing. At this point, we can, on the one hand, expand our database to validate the propositions and, on the other hand, specify the results.

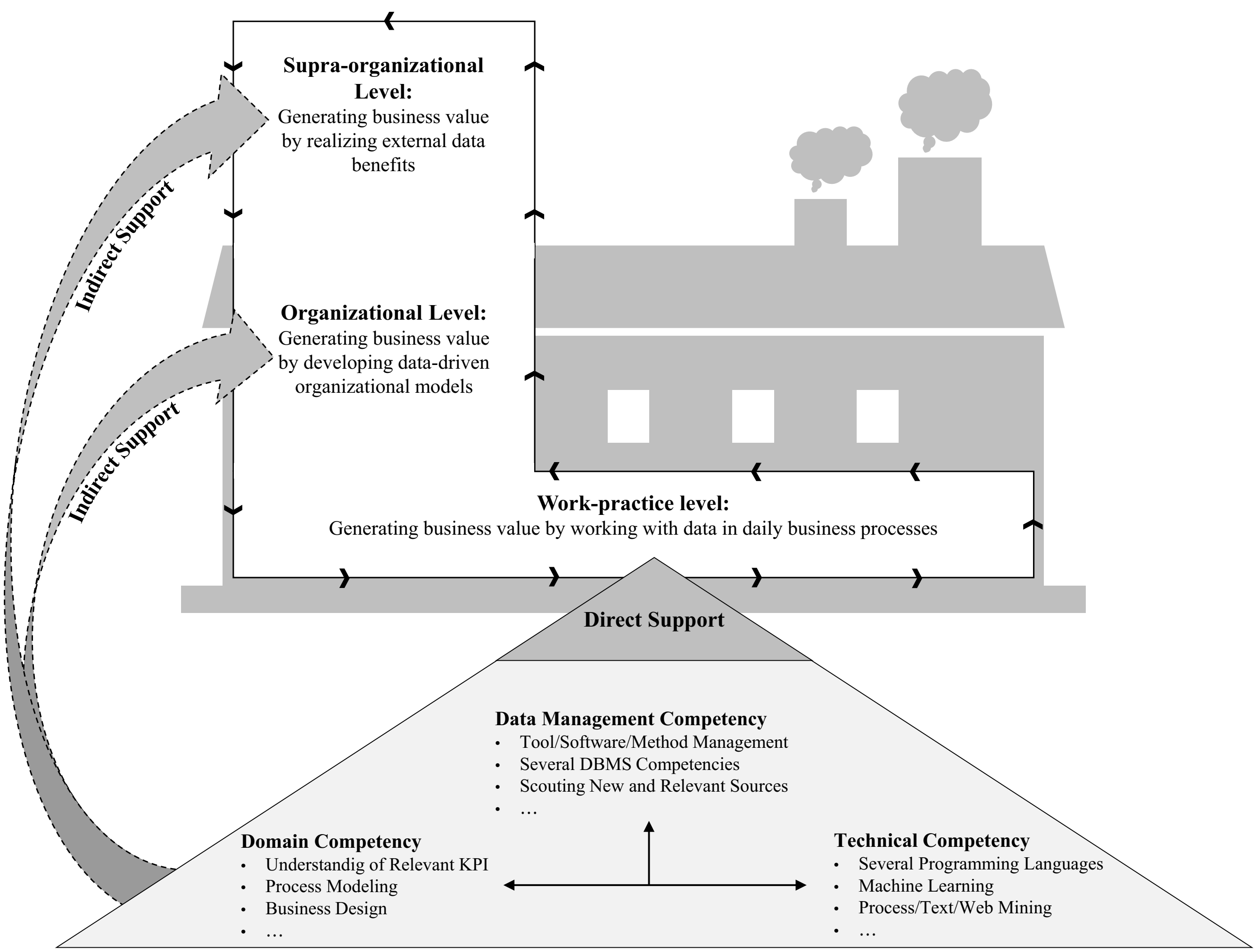

Figure 4.

Conclusion and further steps

We defined data analytics competencies for our research and presented related concepts. We also described value in the context of data analytics with the help of several approaches, including a comment on our decision to build on the multilevel approach of Günther et al. (2017). Furthermore, we presented our methodology by describing the conduct of a systematic literature review and the first conducted expert interviews. As a result, we presented six propositions with regard to the positive effects of data analytics competencies on business value. Within our discussion section, we presented theoretical and practical implications as well as the limitations of our results. As a result, we propose that there are direct positive effects on business value, which can be realized by building up pertinent data analytics competencies on a work-practice level. We also gave a short outlook on primary indirect effects of our extracted data analytics competencies on the organizational and supra-organizational levels according to Günther et al. (2017). Figure 4 summarizes our findings by showing the already outlined levels and the positive effects on business value visualized by connectors. We illustrate our propositions by showing our assumed direct effects on business value with the help of data analytics competencies within the work-practice level. With the help of the dashed connectors, we also illustrate indirect effects on the organizational and supra-organizational levels, according to Günther et al. (2017), which we explained briefly but which were only of minor relevance within this research paper. Finally, we created a concise data analytics competency framework and connected it with potential business values. Thus, we aimed to face the previously mentioned two major challenges, namely necessary justification for data analytics investments and relevant data analytics competencies, to achieve valuable data analytics activities.

For our future steps, we have to ensure that our data analytics competency framework will be dynamic as the development of new technologies and business requirements is. Thus, we have to continuously update our framework with the help of new relevant literature and further expert knowledge. This development will also influence our propositions, which have to updated, expanded or discarded if necessary. At this point, we know our most important research goal. Our propositions demonstrate the necessity of building up relevant data analytics competencies to create business value, but they also show a lack of insights regarding precise business values, which can be used by organizations. These business values are one important aspect for organizations to justify necessary investments in data analytics activities, which is one major challenge from our perspective as already explained above. Taking these aspects into consideration, we see the specification of precise business values as a relevant research mission and as a major step for our research. In this context, the validation of our propositions is crucial and we provide a valuable starting point for the BDA community to do so (see Table 5).

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Notes on contributors

Sven Klee is a researcher and Industrial PhD student at the Information Systems department and Research Center for Information Systems Design (ITeG) at the University of Kassel, Germany. He obtained his M.A. in information systems from the University of Kassel. He works as a project manager for digitalization projects in the procurement department of a German car manufacturer. His research interests focus on data management and data competencies in organizations with a special interest in the field of procurement and relevant application cases.

Andreas Janson is a Postdoctoral Researcher at the Institute of Information Management (IWI-HSG) at the University of St. Gallen, Switzerland. He obtained his PhD from the University of Kassel, Germany. His research focuses on service design, smart personal assistants, decision-making in digital environments, and digital learning. His research has been published in leading information systems and management journals such as the Journal of the Association for Information Systems, European Journal of Information Systems, Journal of Information Technology, and Academy of Management Learning & Education.

Jan Marco Leimeister is a Full Professor and Director at the Institute of Information Management at the University of St. Gallen. He is also Full professor and Chairholder for Information Systems as well as Director of the Research Center for Information System Design at the University of Kassel. His research covers digital business, digital transformation, service engineering, and service management. His research has been published in leading journals such as Information Systems Research, the Journal of Management Information Systems, Journal of the Association for Information Systems, Journal of Information Technology, Information Systems Journal, and the Journal of Strategic Information Systems.

ORCID

Andreas Janson http://orcid.org/0000-0003-3149-0340

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