CONFERENCE ON PRODUCTION SYSTEMS AND LOGISTICS
CPSL 2023

4th Conference on Production Systems and Logistics

Sociotechnical Assessment Of Risks In The Use Of Business Analytics

Jonas Müller[1], Gina Hermes[1], Gerrit Hoeborn[1], Volker Stich[1]
[1]Institute for Industrial Management (FIR) at RWTH Aachen University

Abstract

The use of Business Analytics (BA) helps to improve the quality of decisions and reduces reaction latencies, especially in uncertain and volatile market situations. This expectation leads a continuously rising number of companies to make large investments in BA. The successful use of Business Analytics is increasingly becoming a differentiator. At the same time, the use of BA is not trivial, rather, it is subject to high socio-technical requirements. If these are not addressed, high risks arise that stand in the way of successful use. In particular, it is important to consider the risks in relation to the different types of BA in a differentiated way. So far, there is a lack of suitable approaches in the literature to consider these type-specific risks with regard to the socio-technical dimensions: people, technology, and organization. This paper addresses this gap by initially identifying risks in the use of Business Analytics. For this purpose, possible risks are identified using a systematic literature review and verified with a Delphi survey with various partners experienced in dealing with BA. Subsequently, the identified and validated risks are assigned to three different types of Business Analytics (Descriptive, Predictive and Prescriptive Analytics) and assessed in order to systematically address and reduce the risks. The result of this paper is an overview of the interactions between the socio-technically assigned risks, summarized in a risk catalog, and the different types of Business Analytics.

Keywords

Sociotechnical; Risks; Risk assessment; Business Analytics; Types

1. Introduction

Continuously changing market conditions, the exponential advancement of digital technologies and the profound change in customer requirements demand high adaptability and the making of well-founded decisions with minimal reaction latencies [1-3]. To meet these developments, companies are using data-based information and decision systems with advanced statistical methods and functions (analytics), which are summarized under the name of Business Analytics (BA) [4]. The use of BA supports companies in formulating and achieving strategic, tactical, and operational goals and contributes significantly to data-driven decision-making [5]. The almost unlimited possibilities induce a paradigm shift for global competition and enable maintaining long-term competitiveness [6,7].

The expectation has been a major contributor to the continuous increase in investment for several years, with an annual average growth rate estimated at 14 percent for 2027 [8]. Despite the high expected potential, many companies face major challenges which are induced by the deployment of complex systems and technologies that have a great impact on the organization and its employees. In this context, various organizational, technical, and human risks arise, which overwhelm the companies [9]. This is reflected in a high introduction and implementation failure rate of 65 to 80 percent [3]. To address the high failure rate, it is essential to identify, assess and reduce risks in the use of BA. For this purpose, capabilities must be

DOI: https://doi.org/10.15488/13460
ISSN: 2701-6277

developed in the companies to address the risks and to ensure the successful use of new technologies [10,11]. To achieve this goal, this paper identifies type-specific risks in the use of BA and examines their socio-technical interactions. Thus, an overview of the interactions between the socio-technical assigned risks, summarized in a risk catalog, and the different types of BA can be given.

The remainder of the paper is organized as follows. In section 2, the relevant theoretical background is provided. The state of the art is elaborated on in section 3. The research methodology and the study design are explained in section 4. In section 5, the results of the paper, the risk catalog, and the type-specific relationship matrix are discussed. A conclusion is provided in section 6.

2. Theoretical Background

2.1 Business Analytics

As both information systems and enabling technologies have matured, the prevalence and use of these in enterprises have increased dramatically. The cause and result of this development is the ability to generate and store an exponentially increasing amount of data, which has found use under the umbrella term "Big Data" [1]. The great diversity of application and maturity is reflected in the types Descriptive, Predictive, and Prescriptive Analytics. In this paper, the conceptual understanding, description, and typification are based on [12]. They characterize BA by nine characteristics with a total of 29 features in a morphological box. On this basis, three consistent types are formed and validated [12]. In this understanding, BA as a capability can be defined as follows: "application of 'various techniques, technologies, systems, practices, methodologies, and applications that analyze critical business data' [...] to enable evidence-based problem-solving and recognition within the context of business situations [...]" [13].

2.2 MTO concept

The socio-technical systems approach was developed in the 1950s by [14]. Working in a British mine, it was found that a technological change had a significant impact on the social system [14]. A concept developed by [15] within the framework of socio-technical systems is the MTO concept. It is based on the interaction between the employees, the technical systems, and the organizational structures and processes. The central point of this concept is the work task [15]. The benefits gained by a company using BA depend in particular on the ability to use data and information effectively; the interaction between people, technology, and organization is of fundamental importance in this respect [16]. The design of the successful use of BA can thus be classified in the MTO concept [17].

2.3 Risk

Companies must take risks to seize opportunities [18]. Therefore, responsible handling of these risks must be ensured by successful risk management [19]. To this end, a uniform understanding of risk must first be created. In this paper, the risk is defined as [20] “any possible deviation from a planned state, which must be considered in terms of its cause and effect”. In this context, risk in the narrower sense, the danger of losses, and risk in the broader sense, the chance of winning, is considered [21]. In the context of the objective of this study, this means that only those risks are considered that stand in the way of the successful use of BA. Deviations that have a positive effect on the objective are thus not in focus. Risk management in companies includes all organizational processes that allow the risk management process to run [22]. Based on the risk strategy, this process consists of risk identification, risk analysis and assessment, risk control and risk monitoring, and risk communication [20-23]. Regarding operational information systems and IT security, the content of the risk management process must be adapted to the topic area [20,24]. To this end, starting from the corporate strategy, the objective of IT risk management, including the risk objects and their interactions, is first defined [20].

3. State of the Art

To summarize the state of the art, a Systematic Literature Review (SLR) is conducted. For this, the process by [25] is used. The following search strings were used in the literature review: “Business Analytics”, “Business Intelligence”, and “Big Data Analytics”. These were considered in combination with the terms “risk”, “introduction” and/or “implementation”. Additionally, related terms such as “success factors” and “utilization” were considered. IT security frameworks are considered, but are not the focus of this study, as they take less account of the socio-technical contexts in the use of BA. Based on the combinations of the different search terms, 732 publications were found using Google Scholar, IEEE Explore, and Scopus. The publications found were selected to be relevant based on the title, abstract, and a subsequent reading of the full texts. As a result, the following eleven sources were identified: [3,10,26-34].

The sources found were then analyzed based on the fulfillment of four criteria. The criteria were formed based on the objective of this work. The first two criteria represent, to what extent BA-related risks in the narrower and broader sense are considered and how they are located in the socio-technical system theory. The other criteria reflect whether the models from the literature were developed in a specific context or if they can be applied in general. The degree of fulfillment is evaluated on a 5-level scale. These five levels are “not considered”, “marginally considered”, “partially considered”, “explicitly considered”, and “focus of consideration”. None of the analyzed sources fully consider all aspects. The analysis is not an evaluation of the quality of the publications, but rather a consideration of the fulfillment of the individual criteria. The result of the analysis is shown in Figure 1.

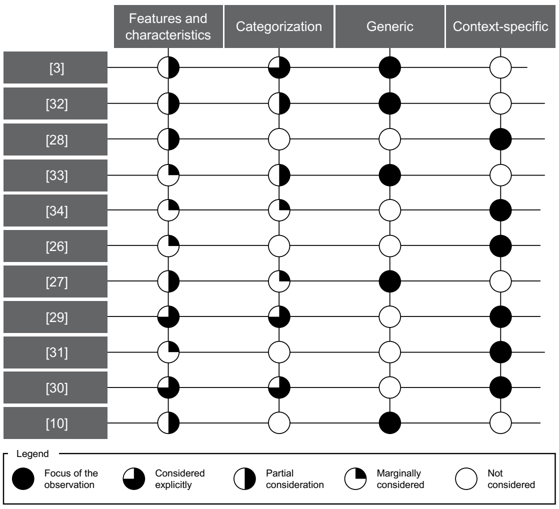

Figure 1: Overview of investigated literature

4. Research Methodology

The Delphi method is an explanatory tool for obtaining a consensus opinion on a topic using interviewing experts. The basic assumption is that the validity of the consensus is higher than that of a single opinion [35]. A central aspect of this method is the multi-stage questioning of experts to gather information on a specific topic [36,37]. The Delphi method begins with the selection of experts, followed by individual rounds of questioning, and finally the analysis of the results [37,38]. Depending on the goal of this method, four different designs can be typified, which are distinguished by seven criteria [38]. In this paper, the design of the Delphi survey is used for idea generation in a qualitative design. The special characteristic of this design is not the consensus of several opinions, but the goal to find a set of ideas for a certain problem solution [38]. In this research, the survey was modified by replacing the initial qualitative survey with a literature review (see chapter 3). The results of the literature review were then presented to the participants as the results of the first round of interviews. The experts could then reflect and contribute additional ideas in the second round of interviews. The second round of questioning was conducted using a workshop and several interviews. A standardized topic-specific dashboard was used as a tool for the survey. After the second round of questioning, the results were collected for the objective of this work and integrated into existing models. A total of seven experts were involved in a workshop and interviews from September to October. All participants were experienced in the use of BA.

5. Results

5.1 Risk catalog

Based on the literature review in chapter 3, 30 different risks related to the use of BA could be identified. With the Delphi survey, all risks could be confirmed. One risk was added during the interviews and was additionally approved in the literature. Thus, 31 socio-technical risks in the use of BA can be summarized in a risk catalog. In the following, the risks are assigned to the three socio-technical dimensions of people, technology, and organization and explained in detail. The result of this step is a risk catalog, see Figure 2.

5.1.1 People

The first dimension to be considered is people. In this dimension, a distinction is made between the risks associated with the *competence of the employees* and the risks associated with *acceptance by the employees*. The first category includes the risk of inadequate employee training and education and low IT skills [3,10,30,32]. If employees are not sufficiently familiar with BA methods or do not have the skills to analyze data correctly, the included data may be insufficient or even incorrect [30]. In addition to this, there is the risk that a user without sufficient experience cannot critically scrutinize the results obtained and does not recognize possible wrong decisions [32]. *Employee acceptance* is divided into possible employee resistance to culture change, the risk of job loss, the risk of lack of team commitment and involvement in BA methods, the risk of change in employees' previous tasks, and employee unwillingness to accept change [10,28,30,33]. The aforementioned risks of *acceptance by employees* are either induced by them or result in them. People often find it difficult to accept innovations, so they would often be against a change in an existing system [30]. In addition, for the successful implementation of BA, certain roles need to be represented by a team, which can change the responsibilities of employees [33]. The permanent risk of job loss for example prevents employees from being open to a possible change, so they may be able to prevent it [30]. In addition to these aspects, as a consequence of low *acceptance by the employee*, the risk of lack of commitment and involvement by the team must be considered. In addition to resistance to a potential culture change, the risk of negative employee attitudes towards change should also be considered in general. This can prevent the decision to use a particular tool even before it is introduced [10].

5.1.2 Technology

The second socio-technical dimension is technology. The risks in this dimension are subdivided into risks that can be assigned to *information technology (IT)* and the risks that affect the *data* as the starting point for the BA application. Concerning the risks of *information technology*, it must be taken into account that, in addition to the risks directly affecting the integration of new systems, general risks can also occur when using IT systems. Thus, it must be ensured that the systemic conditions are sufficient for the use of BA and, at the same time, security risks are taken into account [3,28,31]. This means that integration complexity and technical uncertainties must be mitigated by the infrastructure. In addition, scalability risks must be considered [10,30,34]. If a system is not sized large enough for data collection, it may not be able to collect all relevant data [30]. Finally, it must be considered that innovative methods can lead to risks if they are not sufficiently tested [26]. Therefore, the *IT* risk category consists of the risks of integration complexity, technical uncertainties, scalability risks, IT security due to data protection issues and cyber-attacks, and insufficient IT infrastructure and innovative methods [3,10,26–34]. The risk characteristics of the *data* category are the data source, data quality, and data storage [3,27–30,32–34]. These must be taken into account right from the start of the implementation process [29]. If a risk event occurs in these aspects and, for example, the data quality requirements are not met, effective decision-making may be significantly influenced [32]. The risk concerning the data source and data storage is assumed by the respective medium used. This means that successful implementation is fraught with risk if different media are used, especially media that are not easily compatible [33,29,30].

5.1.3 Organization

The last dimension considered is organization. Risks found here can be divided into the category of *financial* risks and *internal* risks. *Financial* risks can also prevent the implementation of BA, for example, due to the lack of an appropriate budget or the deterrent effect of long payback periods with uncertain returns [10,30]. Another financial aspect that adds some risk to the use of BA is the fact that there are costs that exist only during the application and cannot be estimated beforehand [10]. These hidden costs, when they occur, are an aspect that poses a risk in the use of BA. Thus, the category of financial risks includes large investments in software and hardware, long and uncertain payback periods as well as uncertainty about involved costs [10,30]. The risk characteristics of *internal* risks are insufficient resources, reassignment of employees, quality of business requirements especially the definition of BA deployment objectives, no alignment with business strategy, change management, and regulatory and security changes [3,10,27,29,30,32,33]. In addition to the resources provided by the organization, the general structures also influence the application of BA. For example, a company's change management should be transparent, accountable, and communicated accordingly to avoid concerns about the new technology [3,29]. In addition to this, the reassignment of employees must be done expeditiously, because delays in this organizational task can also be a risk for the integration of BA [30]. Another important aspect is the targeted design of the BA project about the business requirements and the strategy. These two points are important as they directly influence the BA process [3,29,32]. In addition to these two points, regulatory and security standards must also be considered. If such a norm changes, the corresponding tool must also be modified. However, this has for example the consequence, that flexible changes are no longer possible [29]. In addition to this, risks such as the lack of BA application use, insufficient top management support, and no existing knowledge management structure and organizational learning must be considered [3,27,29, 32]. If BA applications are not used sufficiently, the full business potential cannot be exploited [29]. As a result, future investments in BA will be reduced. Another important risk is the lack of top management support. If the relevance of a process is not clearly communicated and the corporate culture is not positively influenced in this direction, the project may fail [3,27,29]. The knowledge management structure and organizational learning are important success factors for the implementation of BA. They are largely responsible for the acquisition and storage of knowledge and thus have a direct impact on the internal data available to BA methods [3]. Lastly, a lack of continuous risk monitoring, static project management, and negative experience with previous IT projects must be considered as risks [3,30,32]. Continuous risk monitoring must be performed to not only be aware of the risks that might arise but also to keep track of them [3]. A lack to identify or address a risk can lead to project failure [21]. It is also important that the project management can react in an agile manner to different situations, otherwise, it hinders the adaptation [32]. Another risk is about the experience with regard to past IT projects. In particular, failed IT projects can lead to the use of a new technology being hindered [30].

socio-technical dimension	risk category	risk characteristic	Descriptive Analytics	Predictive Analytics	Prescriptive Analytics
people	competence of the employees	inadequate employee training and education [3, 30, 32]	-	+	++
		low IT skills [10, 30, 32]	-	+	++
	acceptance by the employees	employee resistande to culture change [30]	-	+	++
		change in employees' previous tasks [28, 30, 33]	-	-	+
		risk of job loss [30]	-	-	+
		lack of team commitment and involvement [30]	+	++	++
		unwillingness to accept change [10, 30]	+	+	++
technology	information technology (IT)	integration complexity [10, 28, 32, 33, 34]	+	+	++
		technical uncertainties [10, 30, 33]	+	+	++
		scalability risks [30]	+	+	+
		IT-security - data protection issues and cyber-attacks [10, 26, 28, 30, 31, 32]	+	++	++
		insufficient IT-infrastructure [3, 10, 27, 28, 29, 30, 31, 32, 33]	-	+	++
		innovative methods [26]	-	+	++
	data	data quality [3, 27, 28, 29, 30, 32, 33, 34]	+	++	++
		data source [29, 30, 33]	+	++	++
		data storage [30]	+	++	++
organization	financial	large investments for software and hardware [30]	-	+	++
		long and uncertain payback periods [10, 30]	-	-	-
		uncertainty about involved costs [10]	-	+	++
	internal	insufficient ressources [3, 29, 30, 33]	+	++	++
		reassignment of employees [10, 30, 33]	+	++	++
		quality of business requirements - definition of BA deployment objectives [29]	+	+	+
		no alignment with business strategy [3, 27, 32]	-	-	+
		change management [3, 29]	+	+	+
		regulatory and security changes [29]	-	-	-
		lack of BA application use [29]	-	+	++
		insufficient top management support [3, 27, 31, 32]	-	+	+
		no existing knowledge management structure and organizational learning [3]	+	+	++
		continuous risk monitoring [3]	-	+	+
		static project management [3, 32]	-	-	+
		negative experience with previous IT projects [33]	-	+	+

Figure 2: risk catalog including relationship matrix

5.2 Relationship matrix

The objective of this study is to identify the link between the socio-technically addressed risks and the different types of BA. For this purpose, the risks are compared with the different BA types against the background of the typification according to [12] to determine the correlation. The comparison is based on the identified risks in the literature and was confirmed by the experts of the Delphi survey. If there is no significant risk between a risk characteristic and the aspects of the BA type, it is characterized by a “-“. However, if there is a medium risk, a “+” is used. High risks can be described with a “++”. Based on this assessment, a total of 52 interactions could be identified. This corresponds to 55,91 percent significant interactions. As a result, the most important socio-technical risks for the individual BA types can be derived from Figure 2.

5.2.1 Descriptive Analytics

The least mature type of BA is Descriptive Analytics. This is also reflected in the characteristics of the risk assessment, in that the fewest significant risks can be assigned here. Aggregated with the risk category level, only *Information Technology* is affected by risks to a significant extent. This is induced by the risk of integration complexity, technical uncertainties, and scalability risks. The evaluation is induced by the value proposition and the analysis methodology as typification aspects. If the integration is particularly complex or the system is not sufficiently scaled, it may result in an insufficient consideration of the cause-effect relationships and thus the goal of descriptive analytics may be missed. Concerning the analysis methodology, the risk of technical uncertainties must also be taken into account. If a company does not have the technology to enable data visualization or statistical analyses, the use of BA will fail. However, at the level of risk characteristics, in addition to *information technology* risks, *internal* organizational risks can also occur in Descriptive Analytics. They include the risk of insufficient resources, the quality of business requirements, and the lack of structure for knowledge management and organizational learning. These risks relate to the direct input parameters of the BA technology, such as the type and structure of the data and, as a further aspect, the analysis methodology. If the respective risk case occurs, it becomes difficult, for example, to provide purely static and structured data. These are mandatory, as Descriptive Analytics methods cannot handle higher complexities. The analytics methodology must also be adapted to the objectives of the BA deployment to provide added value.

5.2.2 Predictive Analytics

The use of Predictive Analytics induces an increase in risks. A relationship can be found between each risk category, except for *employee acceptance*, and the BA type. In contrast to Descriptive Analytics, this BA type is more susceptible to risks due to *employee competence*. This is mainly induced by the comprehensibility of the results of the BA method and the analysis methodology. The results of this BA type are often only partially comprehensible, so employees who are not sufficiently trained have additional problems interpreting them correctly. The analysis methodology, such as data mining, also requires a certain level of IT knowledge for successful application. If an employee cannot use this knowledge, the application is in danger of failing. The increasing complexity or maturity of this BA type is reflected in many aspects of its technical system. In addition to the more complex analysis methods, a larger amount of data is also required, and semi-structured data can be used in addition to structured data. Accordingly, this type is also more susceptible to the risks from the socio-technical dimension of technology. It is noticeable that the socio-technical dimension of technology has a medium risk for the BA type in eight out of nine risks. Another peculiarity at the level of risk characteristics is the link between the risk of insufficient resources and the BA type, this was assessed as high risk and should accordingly be taken into account by the company. Analogous to the type Descriptive Analytics, the risk concerns the input parameters of the BA method. The increase in the number and strength of the risks is justified by the fact that the complexity of the methods and the requirements for the IT infrastructure are increasing. In addition to this, it should be noted that other risk characteristics of the organization may have a greater impact on this type.

5.2.3 Prescriptive Analytics

The last BA type studied is Prescriptive Analytics. It has the most and highest socio-technical risks. In total, 28 out of 31 risks are to be considered for this type. Half of the risk categories were identified as medium risk and the other half as high risk. All risks related to people need to be considered. Due to the type-specific characteristics of the BA method's task, such as automated decision-making or proactive information processing, its previous functions, and future tasks are significantly influenced. This means that the risks may increase, for example, due to the acceptance of the employees and disrupt the successful use. The characteristics of *information technology* and *data* must also be fully considered. Seven out of nine risk characteristics are classified as a high risk for the BA type. As with Predictive Analytics, this can be justified by the higher complexity of this BA type. This is not only caused by the more complex technological aspects, but also by the mature task-specific characteristics, for example, automated decision-making. The socio-technical aspect of the organization has the missing three risk characteristics, these are long and uncertain payback period, change management, as well as regulatory and security change. For these three risks, interactions with individual characteristic features can be considered, but the overall BA type is not sufficiently influenced. For a decision-maker, this means that he does not necessarily have to focus on these aspects when implementing BA. High risk is caused by the characteristics of large investment costs in software and hardware, uncertainty about involved costs, insufficient resources, lack of use of BA applications, and lack of structure for knowledge management and organizational learning. Similar to the remaining risks, these are assessed with a higher risk for Prescriptive Analytics, due to the more extensive task-specific and technological aspects.

6. Conclusion and Outlook

The categorization of risks and the investigation of their interaction can be presented as the result of this paper. Six different risk categories with a total of 31 different risk characteristics were identified in the three socio-technical dimensions. From the various interactions, it becomes apparent which socio-technical dimensions cause risks in the individual types. Best to our knowledge, this is the first overview in research of the socio-technical risks that arise from the use of BA. Overall, it can be concluded that more risks need to be considered the higher the maturity level of the Business Analytics type. In the case of Descriptive Analytics, few risks need to be taken into account; only the risk category of information technology contains a medium risk. These need to be given special consideration. In comparison, in the case of Predictive Analytics, almost all risk categories can induce a medium risk. A special focus should be placed here on the entire socio-technical dimension of technology. The third BA type, Prescriptive Analytics, has the highest risk interference. Accordingly, a comprehensive risk overview and a prior situation analysis should be performed for a successful implementation. In the future, it makes sense to develop possible risk avoidance strategies and make these available to companies.

Acknowledgments

The IGF project 22433 N is funded by the AiF within the framework of the program for the funding of cooperative industrial research by the Federal Ministry for Economic Affairs and Climate Action based on a resolution of the German Bundestag. Any opinions, findings, and recommendations expressed in this paper are those of the authors and do not necessarily reflect the views of the correspondent institutions.

References

[1] Aydiner, A.S., Tatoglu, E., Bayraktar, E., Zaim, S., Delen, D., 2019. Business analytics and firm performance: The mediating role of business process performance. Journal of Business Research 96, 228–237.

[2] Duan, Y., Cao, G., Edwards, J.S., 2020. Understanding the impact of business analytics on innovation. European Journal of Operational Research 281 (3), 673–686.

[3] Müller, J., Schuh, G., Meichsner, D., Gudergan, G., 2020. Success factors for implementing Business Analytics in small and medium enterprises in the food industry, in: 2020 IEEE International Conference on Technology Management, Operations, and Decisions (ICTMOD), Marrakech, Morocco. 24.11.2020 - 27.11.2020. IEEE, pp. 1–8.

[4] Bayrak, T., 2015. A Review of Business Analytics: A Business Enabler or Another Passing Fad. Procedia - Social and Behavioral Sciences 195, 230–239.

[5] Ferraris, A., Mazzoleni, A., Devalle, A., Couturier, J., 2018. Big data analytics capabilities and knowledge management: impact on firm performance. MD 57 (8), 1923–1936.

[6] Arora, B., 2019. Big Data Analytics: The Underlying Technologies Used by Organizations for Value Generation, in: Chahal, H., Jyoti, J., Wirtz, J. (Eds.), Understanding the Role of Business Analytics. Springer Singapore, Singapore, 9-30.

[7] Seddon, P.B., Constantinidis, D., Tamm, T., Dod, H., 2017. How does business analytics contribute to business value? Info Systems J 27 (3), 237–269.

[8] Albertson, M., 2018. Software, not hardware, will catapult big data into a $103B business by 2027. https://siliconangle.com/2018/03/09/big-data-market-hit-103b-2027-services-key-say-analysts-bigdatasv/.

[9] Menzefricke, J.S., Wiederkehr, I., Koldewey, C., Dumitrescu, R., 2021. Socio-technical risk management in the age of digital transformation -identification and analysis of existing approaches. Procedia CIRP 100, 708–713.

[10] Raguseo, E., 2018. Big data technologies: An empirical investigation on their adoption, benefits, and risks for companies. International Journal of Information Management 38 (1), 187–195.

[11] Willcocks, L., Graeser, V., 2001. Delivering IT and eBusiness Value, 1. Aufl. ed. Elsevier professional, s.l., 320 pp.

[12] Müller, J., Schuh, G., Nahr, B., Hoeborn, G., Stich, V., 2023. Understanding Business Analytics: Characteristics and Archetypes. ICTMOD 2022 – in publication

[13] Ashrafi, A., Zare Ravasan, A., Trkman, P., Afshari, S., 2019. The role of business analytics capabilities in bolstering firms' agility and performance. International Journal of Information Management 47 (0), 1–15.

[14] Trist, E.L., Bamforth, K.W., 1951. Some Social and Psychological Consequences of the Longwall Method of Coal-Getting. Human Relations 4 (1), 3–38.

[15] Ulich, E., 2013. Arbeitssysteme als Soziotechnische Systeme - eine Erinnerung. Journal Psychologie des Alltagshandelns / Psychology of Everyday Activity (6).

[16] Schuh, G., Anderl, R., Dumtrescu, R., Krüger, A., Hompel, M. ten, 2020. Industrie 4.0 Maturity Index: Die digitale Transformation von Unternehmen gestalten. Update 2020, München.

[17] Mikalef, P., van de Wetering, R., Krogstie, J., 2019. From Big Data Analytics to Dynamic Capabilities: The Effect of Organizational Inertia.

[18] Königs, H.-P., 2013. IT-Risikomanagement mit System: Praxisorientiertes Management von Informationssicherheits- und IT-Risiken, 4. Aufl. ed. Springer Vieweg, Wiesbaden, 454 pp.

[19] Mahnke, A., Rohlfs, T., 2020. Betriebliches Risikomanagement und Industrieversicherung. Springer Fachmedien Wiesbaden, Wiesbaden, 745 pp.

[20] Romeike, F., Hager, P., 2020. Erfolgsfaktor Risiko-Management 4.0. Springer Fachmedien Wiesbaden, Wiesbaden, 657 pp.

[21] Seidel, M., 2011. Grundlagen und Aufbau eines Risikomanagementsystems, in: Risikomanagement und Risiko-Controlling. Organisation und Dokumentation im Unternehmen, Datenerhebung und Risikobewertung, Integration in die Führungs- und Reportingsysteme, Umsetzungsbeispiele aus der Praxis, 1. Aufl. ed. Haufe Verlag, s.l., pp. 21–50.

[22] Vanini, U. von, 2022. Risikocontrolling in der Unternehmenspraxis, in: Becker, W., Ulrich, P. (Eds.), Handbuch Controlling. Springer Fachmedien Wiesbaden, Wiesbaden, pp. 271–288.

[23] Spille, J., 2009. Typspezifisches Risikomanagemnt für die Beschaffung von Produktionsmaterialien in der Automobilzulieferindustrie, 135 pp.

[24] Adelmeyer, M., Petrick, C., Teuteberg, F., 2018. IT-Risikomanagement von Cloud-Services in kritischen Infrastrukturen: HMD Best Paper Award 2017. Springer Vieweg, Wiesbaden, Heidelberg, 38 pp.

[25] Vom Brocke, J., Simons, A., Niehaves, B., Niehaves, B., Reimer, K., Plattfaut, R., Cleven, A., 2009. Reconstructing the Giant: On the Importance of Rigour in Documenting the Literature Search Process, in: Information systems in a globalising world. ECIS 2009, 17th European Conference on Information Systems, Verona, May 08 - 10 June, 2009; proceedings, Verona.

[26] Baars, H., Kemper, H.-G., 2021. Business Intelligence & Analytics – Grundlagen und praktische Anwendungen. Springer Fachmedien Wiesbaden, Wiesbaden, 459 pp.

[27] Cruz-Jesus, F., Oliveira, T., Naranjo, M., 2018. Understanding the Adoption of Business Analytics and Intelligence, in: Rocha, Á., Adeli, H., Reis, L.P., Costanzo, S. (Eds.), Trends and advances in information systems and technologies. Volume 1. Springer International Publishing, Cham, pp. 1094–1103.

[28] Fischer, T.M., Lueg, K.-E., Steuernagel, M., Mauch-Maier, B., Hofbeck, D., Schneck, L., 2020. Business Analytics in Shared Service Organisationen, in: Fischer, T.M., Lueg, K.-E. (Eds.), Erfolgreiche Digitale Transformation von Shared Services. Springer Fachmedien Wiesbaden, Wiesbaden, pp. 147–187.

[29] Gangotra, A., Shankar, R., 2016. Strategies in managing risks in the adoption of business analytics practices. Journal of Enterprise Information Management 29 (3), 374–399.

[30] Kusi-Sarpong, S., Orji, I.J., Gupta, H., Kunc, M., 2021. Risks associated with the implementation of big data analytics in sustainable supply chains. Omega 105, 102502.

[31] Min, H., Joo, H.-Y., Choi, S.-B., 2021. Success Factors Affecting the Intention to Use Business Analytics: An Empirical Study. Journal of Business Analytics 4 (2), 77–90.

[32] Pabinger, D., Mayr, S., 2019. Controlling und Business Intelligence & Analytics, in: Feldbauer-Durstmüller, B., Mayr, S. (Eds.), Controlling - Aktuelle Entwicklungen und Herausforderungen. Digitalisierung, Nachhaltigkeit und Spezialaspekte. Springer Gabler, Wiesbaden, Heidelberg, pp. 83–106.

[33] Seiter, M., 2017. Business Analytics: Effektive Nutzung fortschrittlicher Algorithmen in der Unternehmenssteuerung, [1. Auflage] ed. Verlag Franz Vahlen, München, VIII, 233 Seiten.

[34] Woratschek, H., Borgdorf, U., Dornbusch, D., Finken, T., Große, C., Haefs, R., Knocke, H., Stopa, P., Vollmer, M., Wilhelm, J.B., Schneck, L., 2020. Implementierung digitaler Prozesse, in: Fischer, T.M., Lueg, K.-E. (Eds.), Erfolgreiche Digitale Transformation von Shared Services. Springer Fachmedien Wiesbaden, Wiesbaden, pp. 19–47.

[35] Köck-Hódi, S., Mayer, H., 2013. Die Delphi-Methode. ProCare 18 (5), 16–20.

[36] Burkhard, U., Schecker, H., 2013. Curriculare Delphi-Studien, in: Krüger, D., Parchmann, I., Schecker, H. (Eds.), Methoden in der naturwissenschaftsdidaktischen Forschung. Springer Berlin Heidelberg, Berlin, Heidelberg.

[37] Demeter, P., 2015. Near Field Communication im Handel: Expertenbefragung mittels Delphi-Methode. HMD 52 (2), 240–248.

[38] Häder, M., 2021. Delphi-Analyse, in: Zerres, C. (Ed.), Handbuch Marketing-Controlling. Grundlagen, Methoden, Umsetzung, 5., erweiterte und überarbeitete Auflage ed. Springer Gabler, Berlin, Heidelberg.

Biography

Jonas Müller, M. Sc., has been a research associate and project manager at FIR e. V. at RWTH Aachen University since 2018. There, he is working in the topic area of business transformation on the strategies, phenomena, capabilities, processes, and methods of transforming companies in the digitally networked economy. A particular focus is on the socio-technical design of the use of Business Analytics.

Gina Hermes, B. Sc, has been a student of industrial engineering specializing in mechanical engineering at RWTH Aachen University since 2016. She completed the corresponding bachelor's degree program in 2021 and is now writing her master's thesis at FIR e. V.. The focus of her work is on the investigation of Business Analytics-related risks.

Gerrit Hoeborn, M. Sc. M. Sc., is head of the business transformation department at RWTH Aachen University. He joined the department after his studies in industrial engineering at the RWTH Aachen University and Tsinghua University. His research focus is on business transformation and digital business strategies.

Prof. Dr. -Ing. Volker Stich is head of the Institute for Industrial Management (FIR) at the RWTH Aachen University since 1997. Prof. Dr. -Ing. Volker Stich worked for the St. Gobain Automotive Group for 10 years and led the management of European plant logistics. In addition, he was responsible for the worldwide coordination of vehicle development projects.