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ORIGINAL ARTICLE

Self-service business intelligence and analytics application scenarios: A taxonomy for differentiation

Jens Passlick[1] · Lukas Grützner[1] · Michael Schulz[2] · Michael H. Breitner[1]

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Abstract
Self-service business intelligence and analytics (SSBIA) empowers non-IT users to create reports and analyses independently. SSBIA methods and processes are discussed in the context of an increasing number of application scenarios. However, previous research on SSBIA has made distinctions among these scenarios only to a limited extent. These scenarios include a wide variety of activities ranging from simple data retrieval to the application of complex algorithms and methods of analysis. The question of which dimensions are suitable for differentiating SSBIA application scenarios remains unanswered. In this article, we develop a taxonomy to distinguish among SSBIA applications more effectively by analyzing the relevant scientific literature and current SSBIA tools as well as by conducting a case study in a company. Both researchers and practitioners can use this taxonomy to describe and analyze SSBIA scenarios in further detail. In this way, the opportunities and challenges associated with SSBIA application can be identified more clearly. In addition, we conduct a cluster analysis based on the SSBIA tools thus analyzed. We identify three archetypes that describe typical SSBIA tools. These archetypes identify the application scenarios that are addressed most frequently by SSBIA tool providers. We conclude by highlighting the limitations of this research and suggesting an agenda for future research.

Keywords Self-service · Business intelligence · SSBIA application scenarios · Taxonomy · Software archetypes

1 Introduction

The success of companies often depends on the right decisions being made at the right time. This dependence can apply to both strategic and operational decisions. In this context, the goal of modern companies is to make more decisions based on

✉ Jens Passlick
passlick@iwi.uni-hannover.de

Extended author information available on the last page of the article

facts and figures instead of making purely subjective decisions (Bani-Hani et al. 2019). Information has become an essential asset for companies, necessitating the use of business intelligence (BI) systems for future development to remain competitive (Tavera Romero et al. 2021). This development leads to higher demands on a BI environment, which should provide the information that is necessary for decision-making (Michalczyk et al. 2020). However, easy and flexible access to data is a major problem in conventional BI architectures, as classical BI structures are often too rigid and slow (Imhoff and White 2011; Bani-Hani et al. 2019). Changes to reports and the creation of new analyses are largely the responsibility of the IT department. Enabling business departments to produce reports and analyses on their own may be a solution to this problem (Bani-Hani et al. 2018a). The ability of business departments to create reports and analyses by themselves is often summarized under the term self-service business intelligence (Alpar and Schulz 2016). Requirements in the context of analytics are also added more frequently, which is why the term should now be taken to include self-service business intelligence and analytics (SSBIA) applications (Chen et al. 2012; Michalczyk et al. 2020). For example, business departments increasingly want to identify patterns and outliers in very diverse data. Therefore, it would be helpful if such data analyses could be carried out flexibly and immediately by the business department itself (Passlick et al. 2020). In recent years, software manufacturers have tried to offer increasingly simple and, most importantly, target group-oriented SSBIA tools (Eckerson 2019). The importance of SSBIA has also been demonstrated by surveys such as the "Data, BI & Analytics Trend Monitor" from the Business Application Research Center (BARC 2022). This survey is based on the opinions of 2400 industry practitioners and shows that the implementation of SSBIA has consistently ranked among the top five most important trends over the past 5 years in the area of data management and BI (BARC 2022).

Alpar and Schulz (2016, p. 151) describe the goal of SSBI as to "… empower casual users to perform custom analytics and to derive actionable information from large amounts of multifaceted data without having to involve BI specialists. Power users, on the other hand, can accomplish their tasks with SSBI more easily and quickly than before". Various aspects of an SSBIA approach have been discussed previously. Different perspectives, user roles, experiences, and self-service levels have been investigated in the context of SSBIA research (Michalczyk et al. 2020). In particular, the diverse levels of self-service illustrate how different SSBIA application scenarios can be (Alpar and Schulz 2016). Alpar and Schulz (2016) distinguish these levels based on only two dimensions: self-reliance and system support. In other publications, additional dimensions are addressed to differentiate the levels of self-service further, such as the user roles included or the experiences of the users (Passlick et al. 2017, 2020; Weiler et al. 2019). The necessary data management, which varies in terms of complexity, can be used to make strict distinctions among different SSBIA application scenarios (Imhoff and White 2011). These aspects highlight the research gap regarding the necessity of obtaining a more detailed understanding of the dimensions of SSBIA. The lack of a detailed SSBIA classification and an identification of different application scenarios leads to certain problems. For example, SSBIA application developers must identify the SSBIA level for which they intend to create applications precisely to address the relevant requirements in the best possible way (Johansson et al. 2015). The value of SSBIA for a company is also extremely dependent on the SSBIA application scenarios in question. Previous research has not necessarily taken the stronger differentiation that is made possible by more target group-oriented SSBIA tools into account. In addition, the question of which application scenarios currently exist in practice remains unanswered. To provide a detailed description of these application scenarios, we propose our research question (RQ):

What dimensions and characteristics distinguish SSBIA application scenarios and what scenarios currently exist?

Based on these dimensions and characteristics, various SSBIA applications can be described and investigated more effectively. First, we discuss the literature on SSBIA levels. Subsequently, we develop our taxonomy by using an iterative procedure following the suggestions of Nickerson et al. (2013). For this purpose, we use not only our findings based on previous publications but also our analysis of SSBIA tools and a case study. Thereafter, we deduce our final taxonomy. We continue to investigate the question of which SSBIA applications are supported by SSBIA tools currently on the market. Using our taxonomy, we classify these tools and conduct a cluster analysis. Based on the clusters thus discovered, archetypes can be formed that allow conclusions to be drawn regarding the SSBIA application scenarios that are increasingly being addressed by SSBIA tool providers. Finally, we discuss our results and findings, their implications, the resulting recommendations, and the limitations of this research; we also highlight further research opportunities.

2 Knowledge regarding SSBIA dimensions

Throughout the remainder of this article, we refer to the definition of SSBIA by Alpar and Schulz (2016, p. 151) as the empowerment of "casual users to perform custom analytics and to derive actionable information from large amounts of multifaceted data". In this context, analytics includes the use of advanced algorithms and analytic models for diagnostic, predictive, or prescriptive purposes (Moore 2017). However, the important factor in this context is that end users can take advantage of these applications despite the fact that their job descriptions do not primarily involve statistical or analytical activities (Moore 2017). This empowerment can be the key to allowing organizations to become data-driven organizations (Mullarkey et al. 2019). Research has focused on different aspects of SSBIA. Imhoff and White (2011) conduct a survey to identify the relevant challenges and opportunities from a practical perspective. These challenges and opportunities can be summarized in terms of the ease of use of the software, the accessibility of the data, data management, and easy deployment (Imhoff and White 2011). Johansson et al. (2015) differentiate SSBIA from traditional BI using the PACT framework. The PACT framework comprises the dimensions People, Activity, Context, and Technology (Benyon 2014). A frequently quoted article by Alpar and Schulz (2016) offers a first overview of SSBIA. Alpar and Schulz (2016) describe various levels of SSBIA. They differentiate these levels based on the dimensions "system support" and "self-reliance" (Alpar and Schulz 2016). Figure 1 shows the levels addressed and the dimensions by which they are differentiated.

These three levels can easily be differentiated based on these two dimensions. The question of whether further dimensions are necessary to differentiate SSBIA applications in other contexts remains open. Ogushi and Schulz (2016) conduct a literature analysis to identify the dimensions of technology, data, presentation, and social features. Bani-Hani et al. (2019) analyze business employees' independence and the value that is cocreated in this context. Similar to the findings of Alpar and Schulz (2016), they identify three constellations of SSBIA that create value. These constellations differ based on how independent from the IT department business users are able to work. However, the steps these authors identify are slightly different. They differ based on whether business users are responsible for interpretation (level C), analysis and visualization (level B), or data preparation and gathering (level A) (Bani-Hani et al. 2019). Based on a literature analysis, Lennerholt and van Laere (2019) analyze the challenges of introducing SSBIA. These authors identify the accessibility and usability of data as well as data quality as major groups associated with the challenges of introducing SSBIA (Lennerholt and van Laere 2019). Thus, they identify completely different dimensions than those identified by Alpar and Schulz (2016). Michalczyk et al. (2020) analyze the SSBIA research conducted to date. These authors categorize the literature according to different levels of self-service. For this purpose, they use the levels identified by Alpar and Schulz (2016). They also use the dimensions of perspective, user role, and experience for such differentiation. In this context, other dimensions are also used. The importance of SSBIA efforts with respect to addressing various user types is evident in various works by Eckerson (2012, 2014, 2019). These user types are related to different analytical tools.

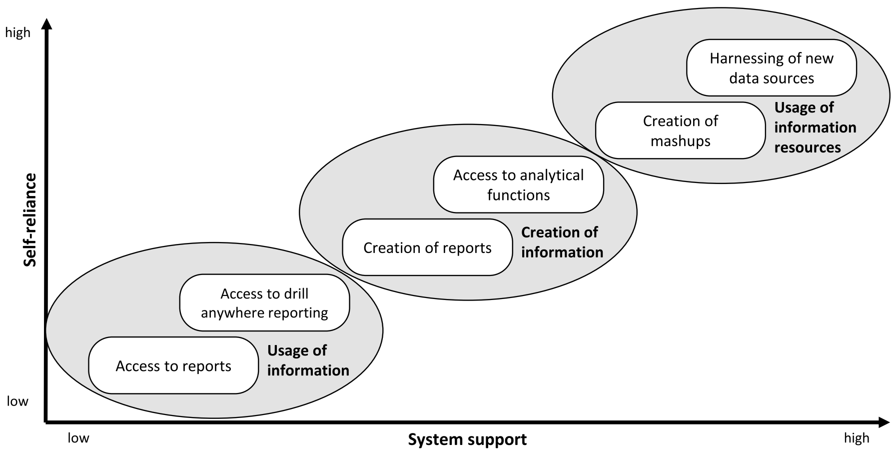

Fig. 1 Differentiation of SSBIA levels according to Alpar and Schulz (2016, p. 152)

In the maturity model developed by Halper (2017), other SSBIA dimensions are once again described. These dimensions are known as organization, data management, infrastructure, analytics, and governance (Halper 2017). However, this model does not classify individual SSBIA application scenarios but rather describes the maturity of the entire organization with regard to SSBIA, e.g., the extent to which an SSBIA culture prevails in the company; however, this factor is not directly relevant to our objectives.

It can be seen that SSBIA has previous been discussed from different perspectives. Various dimensions have been identified, thus highlighting the different requirements for an SSBIA environment that emerge depending on the application in question. However, a clear approach to the task of differentiating these application scenarios has not yet been developed. The work of Alpar and Schulz (2016) provides preliminary insights, but the literature described above shows that many different perspectives on SSBIA can be adopted with respect to the possible applications that can be differentiated. Furthermore, an increasing number of companies are also addressing this topic and discussing the use of SSBIA in different areas (Gartner 2018). Our research addresses this research gap and the associated needs.

3 Development of the taxonomy

3.1 Research design and methodology

"A fundamental problem in many disciplines is the classification of objects of interest into taxonomies" (Nickerson et al. 2013, p. 336). Classification systems such as taxonomies, which are often referred to as typologies, help by structuring and organizing knowledge. Taxonomies uncover and classify objects based on common characteristics and explain their correlations to each other, which allows researchers to understand and analyze complex fields (Glass and Vessey 1995; Varshney et al. 2015; Nickerson et al. 2013; Miller and Roth 1994). Our goal is to create more structure with regard to the wide range of SSBIA application scenarios. Thus, the development of a taxonomy is suitable to improve our ability to differentiate among various SSBIA application scenarios. The design of our taxonomy is based on the methodology for the development of a taxonomy created by Nickerson et al. (2013), as this methodology provides a structured and scientifically sound process for the development of taxonomies. This methodology is an iterative process based on both existing theoretical foundations (conceptualization) and empirical evidence (empiricism). The dimensions thus obtained consist of mutually exclusive and collectively exhaustive characteristics. "Mutually exclusive" means that no object has two characteristics within one dimension, while "collectively exhaustive" means that each object has at least one characteristic in each dimension (Nickerson et al. 2013). Taken together, these two attributes of the taxonomy ensure that each object has exactly one single characteristic in each individual dimension. Starting with an analysis of the literature on SSBIA elements, the dimensions of the taxonomy are derived conceptually. Subsequently, related characteristics are identified by examining SSBIA tools empirically. After each iterative step, multiple ending conditions are checked. If the ending conditions do not entirely apply, a further iterative step is necessary. The ending conditions applied in this process were taken from Nickerson et al. (2013) (see Appendix 8.1). We also conducted a case study. The development of a taxonomy is derived from artifact development in design science research (Hevner et al. 2004; Nickerson et al. 2013). In design science research, evaluation and/or demonstration is an essential component of the research process. A framework for the evaluation of taxonomies has been developed by Szopinski et al. (2019). According to this framework, there are different ways in which a taxonomy can be evaluated. We follow this framework and evaluate our taxonomy using an "illustrative scenario" in Sect. 5 (Szopinski et al. 2019, p. 13). Our procedure is illustrated in Fig. 2.

3.2 Conceptual-to-empirical taxonomy development

In accordance with the suggestions of Nickerson et al. (2013), we base our meta-characteristic on the purpose of the taxonomy in line with our RQ. Therefore, we define our meta-characteristic as follows: the definition of SSBIA dimensions that can help differentiate among SSBIA application scenarios. We specify that the requirements of data science applications are considered to be SSBIA only if they can be realized in the context of analysis applications (Bani-Hani et al. 2019; Eckerson 2019). If the analyses are implemented completely in a programming language, e.g., in Python or R, we consider them to represent an IT implementation and thus no longer an SSBIA scenario. However, the partial use of programming language in analytical applications can constitute an SSBIA scenario, for example, if small snippets of code are used for the specific visualization of data. According to this definition, e.g., the work of a "citizen data scientist" belongs among SSBIA applications (Mullarkey et al. 2019).

The first iteration employs the conceptual-empirical approach of the process model (Nickerson et al. 2013). Possible dimensions that do not match the meta-features are discarded. Given the rapidly increasing number of potentially relevant scientific publications, not all of which add value to a literature review, it is important to identify the most relevant papers (vom Brocke et al. 2015). To

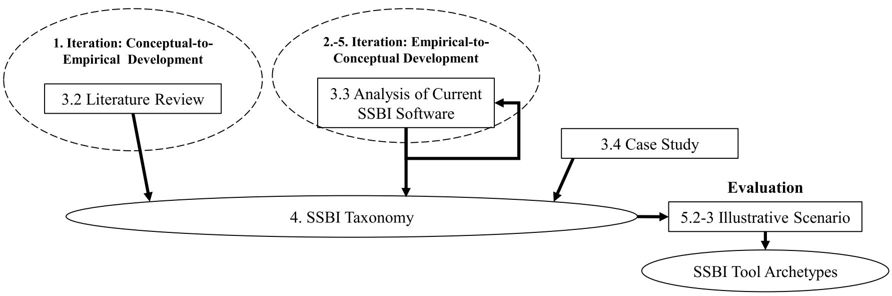

Fig. 2 Performed steps in the process of taxonomy development

identify the relevant literature, we followed the literature review guidelines suggested by Webster and Watson (2002) and vom Brocke et al. (2015).

The purpose of this study is to uncover the differentiating dimensions and characteristics of SSBIA. Consequently, based on this framework, many areas of SSBIA could be considered, leading to our broad characteristic search string "Self-Service Business Intelligence" OR "Self-Service Analytics" OR "Self-Service Business Analytics". Using this search string, the literature search engines and databases ScienceDirect, AiSeL, and Google Scholar were searched systematically, resulting in 46 relevant papers. We conducted a forward (3 papers), backward (4 papers), and a related article search (1 paper), to find additional literature based on the key papers previously identified. The key papers are Alpar and Schulz (2016), Bani-Hani et al. (2017, 2019), Burke et al. (2016), Eckerson (2009, 2012, 2014, 2019), Halper (2017), Imhoff and White (2011), and Lennerholt et al. (2018). These steps allowed us to complete our list, resulting in a total of 54 relevant papers. In addition, we searched the publication lists of the authors Bani-Hani and Eckerson for additional relevant articles. An overview of the overall and final results of these search methods is provided in the table in Appendix 8.2.

Based on the SSBI architecture developed by Passlick et al. (2017), which indicates the relationships between new self-service elements and traditional BI components, we used the five themes of "Data Modeling", "Data Presentation and Analysis", "Users", "Data Governance", and "Architectural Elements" as our first criteria to sort and classify the literature identified. "Data Modeling" describes the tools, components, and techniques that are necessary to transform the data so that it can be analyzed in subsequent steps. The "Data Presentation and Analysis" topic focuses on these further analyses. Tools and techniques that present and visualize data are outlined. The "Users" topic specifies the user groups that can be found in an SSBIA environment. "Data governance" summarizes the guidelines governing, e.g., data quality or data protection. Under the theme of "Architecture Elements", we summarize the components that support SSBIA from a technical or organizational perspective.

To obtain a scientifically valid basis for classifying SSBIA applications, we identified the initial dimensions based on the literature review presented in Table 1. Drawing on the aforementioned SSBIA architecture developed by Passlick et al. (2017), we structured the dimensions of the taxonomy in line with the literature review, resulting in a preliminary taxonomy including a total of eight dimensions. A description of the dimensions follows in Sect. 4, and definitions of the different dimensions can be found in Appendix 8.3. As shown in Appendix 8.1, several end conditions were not met due to the purely conceptual-empirical approach previously employed.

3.3 Empirical-to-conceptual taxonomy development

Subsequently, we employed an empirical-to-conceptual approach. For this purpose, we analyzed SSBIA tools. To identify possible tools, we used Gartner's Magic Quadrant Report (2019), the "BI Products List" drawn from the website

Table 1 Occurrence of perspectives on SSBIA in the literature

	Data modeling	Data presentation and analysis	User	Data governance	Architecture elements
Abelló et al. (2013)	x	x		x	x
Alpar and Schulz (2016)		x	x	x	
Bani-Hani et al. (2017)		x	x		x
Bani-Hani et al. (2018a)		x	x		x
Bani-Hani et al. (2018b)		x	x		x
Bani-Hani et al. (2019)		x	x		
Berthold et al. (2010)		x	x	x	x
Böhringer et al (2009)		x		x	x
Burke et al. (2016)		x	x		x
Burnay et al. (2014)			x		
Clarke et al. (2016)			x		
Convertino and Echenique (2017)			x		
Corral et al. (2015)		x		x	
Daradkeh (2019)		x	x		
De Mauro et al. (2018)			x		
Eckerson (2009)		x	x	x	
Eckerson (2011)	x	x	x		x
Eckerson (2012)		x	x	x	
Eckerson (2014)			x		
Eckerson (2019)		x	x		x
Goeken et al. (2014)		x	x		
Halper (2017)	x	x		x	x
Horvath et al. (2014)		x			x
Howson (2015)	x	x		x	
Imhoff and White (2011)	x	x	x	x	
Johannessen and Fuglseth (2016)	x		x	x	
Johansson et al. (2015)		x	x		
Kobielus et al. (2009)		x	x		
Kosambia (2008)				x	
Kretzer et al. (2015a)		x			
Kretzer et al. (2015b)		x		x	
Lennerholt and van Laere (2019)	x		x	x	
Lennerholt et al. (2018)		x	x	x	
Li et al. (2017)		x	x		
Liu et al. (2012)		x		x	x
Mayer et al. (2014)		x			x
Meyers (2014)		x	x	x	
Michalczyk et al. (2020)	x		x	x	
Morton et al. (2014)	x	x	x	x	
Naish (2013)				x	

Table 1 (continued)

	Data modeling	Data presentation and analysis	User	Data governance	Architecture elements
Ogushi and Schulz (2016)		x			x
Passlick et al. (2017)		x	x	x	x
Pickering and Gupta (2015)		x	x	x	
Poonnawat and Lehmann (2014)		x	x		
Savinov (2014)	x	x	x	x	
Schlesinger and Rahman (2016)		x	x		x
Schuff et al. (2018)				x	
Smuts et al. (2015)		x	x		
Spahn et al. (2008)		x			x
Stodder (2015)		x	x	x	
Stone and Woodcock (2014)		x	x	x	
Sulaiman et al. (2013)		x	x		x
Tona and Carlsson (2013)					x
Vance et al. (2015)				x	
Varga et al. (2014)		x		x	
Weber (2013)		x	x	x	
Weiler et al. (2019)		x	x		
Yu et al. (2013)		x	x		
Zaghloul et al. (2013)	x	x		x	
Zilli (2014)		x			
Zorrilla and García-Saiz (2013)		x			x
Total	*11*	*48*	*40*	*30*	*20*

"BI-Survey.com", the Google search engine using the search strings ("Self-Service Analytics" OR "Self-Service Data Mining" OR "Self-Service Data Preparation" OR "Self-Service Intelligence", and our own knowledge of this field. We found 49 software products that were labeled SSBIA tools. The table in Appendix 8.4 provides an overview of this process. After identifying the SSBIA tools, we checked the website for each tool to verify that the tools could be used to perform SSBIA in accordance with our definition. Two tools were dropped because they did not support SSBIA. This process led to the final sample size of 47 SSBIA tools, which can be seen in Appendix 8.5. The companies developing the tools ranged from mid-sized companies, such as Phocas, to large corporations, such as Microsoft. To analyze the 47 tools thus found, we examined each company's website (websites, online interviews, and videos), product sheets, case studies, and white papers.

Based on this examination of the SSBIA tools, we performed the next five iterations of the process model developed by Nickerson et al. (2013) until we finally fulfilled all ending conditions. In the second and third iterations, we examined a sample of 10 randomly selected SSBIA tools each, from which we derived suitable features pertaining to the dimensions obtained in the first iteration. Furthermore, very similar characteristics that were referred to by different terms were combined into one overall characteristic. In the fourth iteration, we examined a larger random sample of the 15 remaining SSBIA tools to confirm whether the dimensions and characteristics identified during the first three iterations were sufficiently stable, i.e., whether a sufficient number of characteristics had been found and whether they had been reasonably selected. We added additional characteristics and altered the structures of four dimensions from flat to hierarchal. Due to minor additions and changes, the final criteria of the taxonomy were not met.

3.4 Case study

At this point, the development of the taxonomy, which was mainly based on the analysis of SSBIA tools, was formally completed. However, certain important SSBIA aspects are difficult to analyze by reference to empirical data. For example, data governance continues to be discussed in the literature as an important element of SSBIA. Whether SSBIA application scenarios can be differentiated based on data governance remains unclear. The different aspects of data governance are very difficult or even impossible to identify. For this reason, we also conducted a case study. Based on this case study, it can be determined whether different SSBIA applications emerge depending on, e.g., the data governance. In this case study, we investigated the SSBIA application scenarios that are available or planned. Therefore, we identified which SSBIA tool is used and why and how it is used. Several informal, unstructured interviews were conducted with different employees of the case study company, taking into account the guidance provided by Yin (2009). These employees had different roles, including executive positions, BI managers and BI users from the business departments.

The company under investigation is active in the field of engineering and manufacturing, its headquarters is located in Germany. With approximately 4000 employees worldwide, it is considered to be a medium-sized company. The company is thus large enough that it features quite different SSBIA applications. In the context of this study, we examined only BI tools that include SSBIA components.

The company's BI architecture is based on a core data warehouse (DW), which mainly processes data from the enterprise resource planning (ERP) system. To facilitate access to the DW data, different departments use different, predefined queries. The DW data is often processed using Excel. A web front-end is available for this purpose ("SAP BEx Web Analyzer"), which allows to filter data, analyze it by different dimensions and download it in the desired form. In addition, a plug-in for Excel is available ("SAP Analysis for Microsoft Office") to facilitate direct access to queries. This plug-in is increasingly used by financial analysts since some of them are very well trained in Excel and can employ the plug-in efficiently. Furthermore, users experience sufficient freedom in these scenarios to create ad hoc analyses quickly.

To simplify access to the data further and facilitate more efficient interaction, selected applications are created by the IT department on the "Jedox" platform.

The results are web-based dashboards with, in part, very extensive functions for different business areas. For the sales department, some kind of data mart is developed, which is supplied with data from the core DW. In this context, the data modeling is done by the IT department, while small dashboard modifications are implemented by selected power users in the sales department.

One novelty is the requirement for different departments to introduce an additional tool for SSBIA application scenarios. From the perspectives of these departments, the existing tools are somewhat too inflexible (web-based applications), there are no up-to-date visualizations ("Microsoft Excel"), and the tools do not offer interfaces for complex algorithms (sales reporting). "Microsoft Power BI" is discussed in this context as a possible all-round SSBIA tool that can meet these requirements. However, while examining the tool concretely, it became clear that other challenges also arise. For example, when using the tool in the cloud, the role and authorization management implemented in the core DW is bypassed because the data is accessed by a technical user. Permissions can also be bypassed using "Microsoft Excel" worksheets, but the extent of this issue is different. With regard to particularly sensitive data, downloads to "Microsoft Excel" are prohibited. This situation highlights the fact that SSBIA application scenarios can also be differentiated based on the sensitivity of the data. While less critical data can be analyzed group-wide using any tool without major difficulties, access to sensitive data is restricted. With regard to sensitive data, it is necessary to ensure throughout the SSBIA analysis process that the only persons who have access are those who are authorized to do so. Under certain circumstances, these requirements can lead to a situation in which a certain SSBIA tool cannot be used.

Another question that arises when discussing "Microsoft Power BI" pertains to the task of ensuring that correct information is displayed in the applications. This problem applies to SSBIA in general. Data provided by IT are usually tested extensively; thus, their correctness can be assumed. When using queries of the core DW, the sales DW, and the web-based dashboards, the information is reliable, as the modeling is conducted by IT. When using "Microsoft Power BI", data reliability depends on the application scenario. It is possible that the data modeling is largely performed by the business department, in which case data quality is not necessarily guaranteed. The likely data quality depends largely on the complexity of the modeling, the possible transformations, and the completeness of the data.

Our case study shows how SSBIA application scenarios are discussed in the context of a concrete company. The dimensions thus described are also included in this discussion. The next step is to evaluate the usefulness of the taxonomy in further detail.

3.5 Evaluation

We evaluate the developed taxonomy based on the framework developed by Szopinski et al. (2019). For this purpose, we have chosen to employ a quantitative approach and the "illustrative scenario" methodology. More precisely, we have applied "a taxonomy to real-world objects". As described by Szopinski et al. (2019, p. 11), this method of evaluation is appropriate because it "allows researchers to evaluate their practical applicability and usefulness for classifying, differentiating, and comparing objects […] as well as to evaluate their robustness, utility, efficacy, stability, and completeness". In this evaluation, our primary purpose is to investigate whether the developed taxonomy is useful with respect to achieving the goal of differentiating SSBIA applications. Accordingly, we assign all examined SSBIA tools to the characteristics we discovered and conduct a cluster analysis based on this process. This approach allows us to answer the questions of "how?" and "what?" included in the Szopinski et al. (2019) framework. The question of "who?" is answered by reference to the fact that we, as the authors, conduct the evaluation. We have experience with the domain and the method, have academic backgrounds and have been involved in the process of taxonomy development. The cluster analysis should indicate that meaningful clusters ultimately emerge, which differentiate themselves based on the dimensions we discovered. Furthermore, we qualitatively examine the extent to which the archetypes resulting from the clusters represent a plausible form of an SSBIA application. If these archetypes can be discussed profitably, it is indicated that the taxonomy is successful in the task of differentiating among SSBIA applications.

The assignment of the SSBIA tools to the particular characteristics of our taxonomy was performed by one author following the guidelines proposed by Yin (2009). Approximately 10% of the tools were analyzed by a second author to ensure a consistent understanding of the definitions. In dimensions for which the assignment of the SSBIA tools to characteristics was not obvious, assignment criteria for the tools were developed. These criteria can be found in Appendix 8.3.

4 SSBIA application scenarios

4.1 Final taxonomy

Following a literature review, an analysis of SSBIA tools and a case study, we developed a taxonomy for SSBIA application scenarios using the development process developed by Nickerson et al. (2013). This taxonomy consists of eight dimensions featuring a total of 31 characteristics. The four dimensions of BI analytics activities, data management requirements, development collaboration, and access type consist of hierarchical levels, as the characteristics in each dimension build on each other. Accordingly, the characteristic of a higher level also includes the lower levels. The other three dimensions, i.e., user roles, user skills, and nature of the analysis, do not possess such a hierarchy.

We split the initial "user" perspective into the two dimensions of user role (Imhoff and White 2011; Eckerson 2014) and user skill (Eckerson 2011; Alpar et al. 2016). This distinct allows us to adopt a more granular perspective on users, as user roles are mainly task-dependent and user skill are mainly person dependent. The first dimension, user role, distinguishes among the SSBIA application scenarios based on three user types, namely, information consumer, information producer and information collaborator, which have different tasks in the SSBIA process (Eckerson 2011; Alpar et al. 2016). The information collaborator user role focuses on unique tasks such as providing guidance and advice to other SSBIA users but can appear in combination with other user roles with respect to a particular person, as the three user types are task-dependent. The next dimension distinguishes users based on their skills. Skills include statistics, coding, data management, visualization and discovery, and reporting skills (Cosic et al. 2012). The next dimension differentiates BI analytical activities (Alpar and Schulz 2016). With regard to pure self-service data-preparation tools, the first characteristic, i.e., no analytical activity (none), applies. On the other hand, there may be application scenarios in which very extensive analytical activities are performed, such as the performance of more complex analyses using clustering algorithms or regressions. Such extensive analysis activities represent the highest level of activity in this dimension. This third dimension is hierarchical, which indicates that the last characteristic also contains the previous characteristics. For example, report creation and visualization contain access and the use of reports. In the fourth dimension, the requirements for data management in the SSBIA case are distinguished (Cosic et al. 2012). In this context, it is possible that a finished data model that can be used directly (first characteristic) already exists but also that very extensive adjustments are necessary, such as data cleansing and enrichment. This situation is the highest hierarchical level associated with its dimension, as the process of removing inconsistencies and errors in the data can take place only after the extract, transform, and load (ETL) process is complete. The next dimension addresses the importance of collaboration among users in the development of SSBIA applications. SSBIA can support such collaboration by providing comment or rating functions on dashboards, e.g., as in Alpar et al. (2015). The manner in which the final SSBIA application is accessed is addressed in the sixth dimension. If a finished application is to be used on mobile devices, e.g., this use case must also be taken into account during the process of development. This additional requirement can also increase the associated complexity further. However, the complexity also depends on the tools used. The next dimension describes what actually drives the SSBIA analysis or report in question (Schulz et al. 2015). The purpose of this process may be to answer an ad hoc question or to develop a regular report. It is also conceivable that the purpose is to conduct experiments by reference to a data set to determine whether it contains relevant information. The characteristic of all-rounder describes application scenarios in which several of the other characteristics apply.

The final taxonomy is shown in Table 2, and a detailed definition of each characteristic is given in Appendix 8.3. In addition, the dimensions in which the characteristics are structured hierarchically are marked. In the final column, the sources of the particular dimensions are listed.

Table 2 Final taxonomy of SSBIA dimensions

Dimension	Characteristic				Hierarchy	Source
User roles	Information consumer	Information producer (power user)		Information collaborator	No	L, C
User skills	Basic	Standard		Advanced	No	L, C, T
BI analytics activities	None	Access to and use of reports	Report creation and data visualization	Application of advanced analytics	Yes	L, C, T
Requirements for data management	Only small changes	Integration and modeling of existing data sources	Integration of new data sources	Data cleansing and enhancement	Yes	L, T
Collaboration in development	No software-supported collaboration	Individualization of other people's reports		Comments Ratings	Yes	L, S
Access type	Desktop	Big display	Mobile	Natural language	Yes	L*, C*, T*
Nature of the analysis	Standard/ scheduled	Ad hoc	Experi-mental	All-rounder	No	L*, T*, C

Based on *L*, Literature; *C*, Case study; *T*, SSBIA tool analysis, * partly

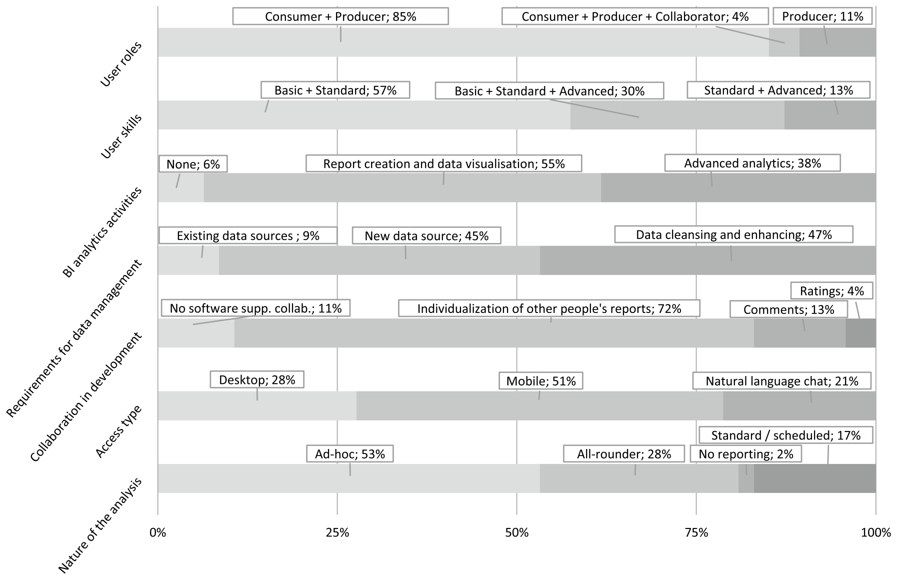

Fig. 3 Frequency distribution of the characteristics of the analyzed tools

4.2 Analysis of the examined data set

To evaluate the taxonomy, all SSBIA tools examined were assigned to their respective characteristics. Figure 3 shows the frequency with which the characteristics were assigned to particular dimensions.

In terms of the user roles dimension, it is apparent that the vast majority of SSBIA tools address both *information consumers* and *information producers*. The *information collaborator* type is not addressed by any tool as the sole characteristic. Eleven percent of the tools focus only on *information producers*. *Basic + standard* is addressed by more than half of the SSBIA tools with respect to the user skills dimension. Thirty percent of the tools additionally include the *advanced* skill. Few tools (13%) do not address the lowest level of skills (*basic*). In the dimension of BI analytics activities, approximately half of the tools are designed for *report creation and data visualization*. Thirty-eight percent of the tools offer additional *advanced analytics* capabilities. At least the *integration of existing data sources* is supported by all SSBIA tools in terms of the dimension requirements for data management. However, approximately 90% of the tools also support further activities. We also identified full support for *data cleansing and enhancing* in 47% of the tools.

Only approximately 11% of the tools do not support any form of collaboration in development. The majority (72%) of the tools support the *individualization of other people's reports*. A small percentage (together approx. 17%) of the tools also offer comment or rating functions. Most tools support access via mobile devices (51%). Approximately 21% even enable *natural language chat*, while 28% offer information access only via *desktop*. With regard to the final dimension investigated, i.e., the nature of the analysis, the ad hoc characteristic dominates, accounting for 53% of the tools, while 28% of the tools try to function as *all-rounders*. Significantly fewer (17%) tools address standard reporting, and 2% of the tools do not have any reporting function because they focus on data preparation.

4.3 Cluster analysis

The assignment of the examined SSBIA tools to the characteristics of our taxonomy described previously was used as the foundation of our cluster analysis. By means of this cluster analysis, we identified typical SSBIA tools that are offered on the market. These typical forms are also known as archetypes. The analysis indicates that the developed taxonomy can differentiate the tools well. In addition, we can obtain insights into the SSBIA application scenarios that are observed by SSBIA tool vendors because they focus their tools on these application scenarios.

To conduct the cluster analysis, we first applied the Ward (1963) algorithm to the collected data set. The Ward (1963) algorithm has the advantage of being a hierarchical partitioning algorithm. In contrast to the k-means algorithm, it is unnecessary to specify the number of clusters to be formed in advance. On the other hand, the clusters formed using k-means are often better. For this reason, a combination of hierarchical and nonhierarchical algorithms is recommended (Balijepally et al. 2011). To apply the Ward (1963) algorithm, we used the Sokal and Michener (1958) matching coefficient to calculate distances. After execution, the result can be

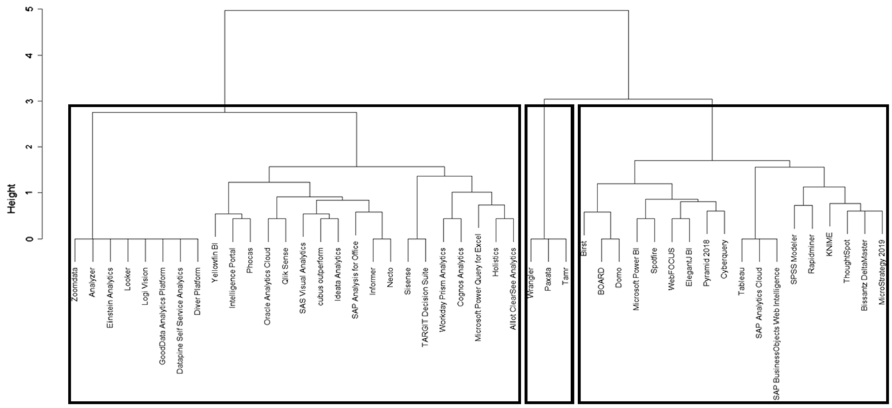

Fig. 4 Clustering using the Ward (1963) algorithm as visualized by a dendrogram

visualized using a dendrogram. This dendrogram is shown in Fig. 4, which displays the SSBIA tools that we analyzed.

All tools are connected by different branches. In this context, if a connection is long, it indicates great differences in the assigned characteristics. The height of the branching gives an impression of how many different groups are included in the data set as well as the strength of that inclusion. At a height of approximately 3, we can see three groups, which could be a suitable cluster number. These three groups are also marked by thicker boxes. However, four clusters would also be conceivable because this junction is at a similar height. The fourth branch is at a height of approximately 2.8, so we continue by using three and four as possible cluster amounts. Two groups would also be conceivable, but if three or four groups already lead to plausible results, these three or four groups are preferable, since the archetypes thus become more differentiated. The data set in this constellation is too small to accommodate more than four groups. Although several measures can calculate the optimal number of clusters, several studies have shown that these measures lead to such different results that a qualitative assessment is more appropriate for our study (Gimpel et al. 2018; Janssen et al. 2020). Accordingly, we analyzed the distribution of the characteristics when separated into three and four groups in further detail. If the study were to be divided into four groups, no plausible groups could be identified. No clear differences could be identified between two of the four groups. We thus concluded that a division into three groups leads to plausible results. The distribution in the case of a separation into three groups is shown in Table 3.

We have assigned each group a label that reflects its essential characteristics. Thereby we refer to the groups or archetypes as *all-rounder with advanced analytics* (A), *simple* ad hoc *application scenarios* (B), and *tools used by information producers* (C). In the *all-rounder with advanced analytics* archetype, all user skills are typically covered by the analyzed SSBIA tools. All analytics and data management activities are typically possible. Most tools support the individualization of other people's reports. Frequently, mobile BI applications can be realized, but many tools of this archetype already include a natural language chat. All kinds of analyses are supported.

In the archetype *simple* ad hoc *application scenarios,* the basic + standard user skill is supported. In rare application scenarios, other skills are also supported. No advanced analytics functions are offered, and data management is limited to the integration of new data sources. The individualization of other people's reports is supported as a form of collaboration, and analyses can usually be accessed via mobile devices. The tools associated with this archetype very often focus on ad hoc analyses.

The user role information producer is the focus of the archetype *tools used by information producers*. Standard + advanced is often addressed as a user skill. The skill basic is therefore rarely included. Either no analytical activities or advanced analytics are enabled. Most such tools support data management with data cleansing and enhancing. Collaboration is frequently not supported. Access to all tools is possible only via desktop. Above all, standard reporting is addressed in this archetype. Table 4 summarizes the archetypes thus found.

5 Discussion, implications, and recommendations

Based on our literature review, our analysis of SSBIA tools, and our case study, we developed a taxonomy that describes different application scenarios of SSBIA. This taxonomy offers a detailed answer to our RQ, which inquires into the dimensions and characteristics that distinguish SSBIA applications. The taxonomy features seven dimensions that are relevant to the task of differentiating SSBIA application scenarios and is evaluated in accordance with the suggestions of Szopinski et al. (2019) by reference to an illustrative scenario.

Based on the dimensions thus uncovered, we expanded the initial differentiation that consists of the two dimensions "self-reliance" and "system support" (Alpar and Schulz 2016). For example, the developed taxonomy concretizes the dimension "self-reliance". The dimensions user skill, BI analytics activities, and requirement for data management can be viewed as an elaboration of "self-reliance", which has implications for both practice and research. Future research can now identify more clearly the particular application scenario of SSBIA in question when investigating aspects of SSBIA. Under certain circumstances, e.g., certain user skills or analytical activities may not be relevant to a research project. The focus of such research can now be differentiated more effectively. The question of whether certain characteristics have a stronger or weaker influence can also be described and analyzed more effectively. For example, experience with BI applications may be even more relevant if the requirements for data management are high, since many factors must be taken into account when performing complex data manipulations. Future research must take these differences into account to provide significantly better tailored SSBIA tools. Our research provides a foundation for a differentiated view of SSBIA. Our literature review in Sect. 3.2 shows that there has been no increase in publications on SSBIA in recent years. This lack of research is astonishing, since SSBIA tools from several years ago are only partly comparable to contemporary tools.

Practitioners can benefit from our taxonomy because it allows them to differentiate among SSBIA application scenarios more effectively. This assistance is

Table 3 Distribution of characteristics among the archetypes

	Label	All-rounder with advanced analytics	Simple ad-hoc application scenarios	Tools used by information producers
	n	18	23	6
	Group	A	B	C
User roles	Consumer + Producer	94%	100%	
	Consumer + Producer + Collaborator	6%		17%
	Producer			83%
User skills	Basic + Standard	33%	91%	
	Basic + Standard + Advanced	67%	4%	17%
	Standard + Advanced		4%	83%
BI analytics activities	None			50%
	Applying advanced analytics	78%	4%	50%
	Report creation and data visualization	22%	96%	
Requirements for data management	Existing data sources	6%	13%	
	New data sources	17%	78%	
	Data cleansing and enhancing	78%	9%	100%
Collaboration in development	Comments	11%	9%	33%
	Individualization of other people's reports	83%	78%	17%
	No software supported collaboration		9%	50%
	Ratings	6%	4%	
Access type	Desktop	6%	26%	100%
	Mobile	56%	61%	
	Natural language chat	39%	13%	
Nature of the analysis	Ad-hoc	28%	87%	
	All-rounder	67%		17%
	No reporting			17%
	Standard / scheduled	6%	13%	67%

Note: Due to rounding inaccuracies, the sum of a column in a dimension is not always exactly 100%.

important for relevant discussions because it addresses issues that are critical to the successful deployment of SSBIA (Passlick et al. 2020). Additionally, to identify the application scenario processes that can be improved using SSBIA, SSBIA application scenarios must be described precisely. The choice of a suitable SSBIA tool is thus also simplified by the taxonomy. Since SSBIA tools have very different focuses, no single tool fits all SSBIA application scenarios (Eckerson 2019).

In addition to this taxonomic knowledge, the analysis of this data set also has other implications. For instance, we can obtain an impression of the properties that are currently addressed by SSBIA software providers. For example, SSBIA tools

Table 4 Identified SSBIA tool types

Label	A All-rounder tools also used for advanced analytics	B Tools used for simple ad hoc application scenarios	C Tools used by information producers (power users)
User roles	Consumer + Producer	Consumer + Producer	Producer
User skills	Basic + Standard + Advanced	Basic + Standard	Standard + Advanced
BI analytics activities	Application of advanced analytics	Report creation and data visualization	None + advanced analytics
Requirements for data management	Data cleansing and enhancement	Integration of new data sources	Data cleansing and enhancement
Collaboration in development	Individualization of other people's reports	Individualization of other people's reports	Primarily no software-supported collaboration
Access type	Primarily mobile, also natural language chat	Mobile	Desktop
Nature of the analysis	All-rounder	Ad hoc	Primary standard/scheduled
Share in sample (47)	38%	49%	13%
Example tool	SAP Analytics Cloud	GoodData Analytics Platform	Paxata

usually offer functions for both information consumers and producers. However, a small percentage (11%) of such tools pertain only to information producers who use the tools to process data with the aim of preparing it for a presentation or using it with other tools. More complex forms of collaboration, such as comments and ratings, have not yet become widespread (17%). Twenty-eight percent of SSBIA tools do not yet support mobile access to data, while 21% even support natural language chat. It is also remarkable that approximately half (53%) of SSBIA tools focus on ad hoc analyses. This finding indicates that many vendors mainly view SSBIA as offering tools for the creation of ad hoc analyses.

The fact that ad hoc analyses play an important role in the analyzed SSBIA tools is also evident in the archetypes we found. In archetype B, i.e., tools for simple ad hoc application scenarios, the primary focus is ad hoc application scenarios, which are rather simple with regard to the analytics activities they involve. According to the differentiation proposed by Alpar and Schulz (2016), the nature of the analysis is not discussed in the levels of SSBIA. However, the high frequency of such characteristics indicates that SSBIA application scenarios must be differentiated based on a number of the dimensions that we provide in our taxonomy. The levels found by Alpar and Schulz

(2016) are also evident in our taxonomy, but our archetypes indicate that the SSBIA application scenarios can also be differentiated in a rather different manner.

Furthermore, certain distinctions among the three user types contained in the first dimension user role are necessary, namely, information consumers, information producers, and information workers, as well as among established roles in the context of general BI & analytics, such as the business user, the data scientist, or the data engineer (Eckerson 2011; Alpar and Schulz 2016; Michalczyk et al. 2021). SSBIA user roles relate exclusively to usage in a business department and offer a granular view of different SSBIA users. These users primarily engage in other main work tasks (Eckerson 2011; Alpar and Schulz 2016), whereas previously established roles in the context of general BI & analytics, e.g., the role of a data scientist, represent a dedicated job definition (Michalczyk et al. 2021).

6 Limitations and directions for future research

When investigating SSBIA tools, it must be kept in mind that they provide conclusions about the SSBIA forms that exist within organizations only indirectly. Aspects such as, for example, the sensitivity of the data indicate that not all such characteristics can be observed in the tools, but the literature as well as, in part, the case study indicate their existence. Namely, SSBIA application scenarios can only be deduced from the advertised functions of SSBIA tools indirectly. For example, in practice, SSBIA application scenarios in which only slight changes must be made to data or data models also emerge, but these scenarios are not mentioned by any software provider, as such small changes do not represent a functionality that must be advertised. Nevertheless, the analysis of SSBIA tools allows conclusions to be drawn regarding the use of SSBIA in companies, as software manufacturers respond to customer demand and adapt their communications accordingly.

The differentiation of SSBIA users, data scientists, and citizen data scientists is not always strictly possible. This problem is also evident with regard to the definition of advanced algorithms. These algorithms can be implemented to a certain extent in the form of a self-service, e.g., a situation in which a citizen data scientist uses a k-means algorithm. However, there are also advanced algorithms that are so complex that they can likely no longer be considered a self-service. For example, the use of artificial neural networks or machine learning can be so complex in terms of their architecture, data management, interpretation, etc., that this approach cannot be considered a self-service. In such scenarios, advanced knowledge is required to construct the models as well as, most particularly, to interpret them correctly. Future research must provide a stronger distinction in this context.

The fact that the characteristics of the SSBIA tools analyzed do not provide any quantitative information regarding the SSBIA application scenarios that are increasingly put into in practice in organizations must also be taken into account. We address this limitation by reference to our case study. However, the case study does not allow for the broad generalization made possible by the analysis of the tools. We conducted only a single-case study to obtain a different perspective on the analysis of the SSBIA tools. Additional companies could be examined in this context for comparison.

Nevertheless, we can draw conclusions regarding practice from the combination of the findings drawn from the literature, the case study, and the analyzed tools. For example, SSBIA seems to be used frequently to conduct ad hoc analyses. Namely, many tools address this activity, and previous research has also identified flexibility and time savings as major advantages of SSBIA (Passlick et al. 2020). For ad hoc analyses, both high flexibility and fast execution are important characteristics.

Findings from the analysis of the SSBIA tools only offer temporary insights. In future research, the analysis must be repeated to identify changes. The focus of SSBIA tool providers changes over time. In contrast, our taxonomy is more time-independent since the dimensions we found are not purely based on the analyzed tools. Nevertheless, future research must determine whether additional characteristics might be added or whether certain elements of the taxonomy might become unnecessary.

7 Conclusions

Our awareness and understanding of SSBIA have changed. Whereas only limited and simple SSBIA application scenarios were initially realized, the goal is now to implement almost all conceivable forms of analysis using SSBIA, even including applications for citizen data scientists. We identify the dimensions that must be considered when investigating and discussing SSBIA application scenarios. Our dimensions include users, their skills, analytical activities, necessary data management, intensity of collaboration, ways of accessing finished reports, and the different types of analysis. Furthermore, we present the different characteristics that pertain to each dimension. Based on the literature, an analysis of SSBIA tools, and a case study in a company, we developed our taxonomy. This approach allowed us to examine SSBIA application scenarios from different perspectives. The taxonomy thus developed is helpful for both research and practice, since a more sophisticated examination of SSBIA scenarios is now possible. Thus, the fact that the opportunities and challenges of SSBIA applications can be quite different depending on the scenario in question can be described and analyzed.

In addition to this taxonomy, our cluster analysis also identified certain archetypes of SSBIA tools. All-round tools that are also suitable for advanced analyses, tools for simple ad hoc analyses, and tools intended for the use by the user group information producers in particular were found in the data set. Our archetypes confirm that the developers of SSBIA tools also address different SSBIA application scenarios. These archetypes indicate that when discussing SSBIA, it is necessary to identify the particular application scenario in question.

Appendix

Summary of fulfilled ending conditions per iteration based on Nickerson et al. (2013)

Iteration					Ending conditions
1. con.*	2. emp.*	3. emp.*	4. emp.*	5. emp.*	
	•	•	•	•	Concise
			•	•	Robust
				•	Comprehensive
•	•	•	•	•	Extendible
		•	•	•	Explanatory
				•	All objects or a representative sample of objects have been examined
•	•	•	•	•	No object was merged with a similar object or split into multiple objects in the last iteration
	•	•	•	•	At least one object is classified under every characteristics of every dimension
				•	No new dimensions or characteristics were added in the last iteration
			•	•	No dimensions or characteristics were merged or split in the last iteration
•	•	•	•	•	Every dimension is unique and not repeated (i.e., there is no dimension duplication)
		•	•	•	Every characteristic is unique within its dimension (i.e., there is no characteristic duplication within a dimension)
	•	•	•	•	Each cell (combination of characteristics) is unique and is not repeated (i.e., there is no cell duplication)

**con.* = conceptual; *emp.* = empirical.

Literature search results

Used database	ScienceDirect	AISel	Google Scholar
Search string	"Self-Service Business Intelligence" OR "Self-Service Analytics" OR "Self-Service Business Analytics"		
Order/ Reviewed	Relevance	Relevance First 12 pages	Relevance First 20 pages
1. Results	58	5827	1700
	Examination of relevance by reading the title, abstract, and deletion of duplicated papers		
2. Results	46		
Forward search	3		
Backward search	4		
Related article search	1		
Final results	54 articles, books, and conference papers in total		

Definition of the found characteristics

Characteristic	Definition	Criteria for the assignment of the software
User roles This Dimension describes the division of SSBIA business user types into distinctive categories based on their specific work task (Eckerson 2011; Alpar et al. 2016).		
Information Consumer (casual)	Casual BI Users who gather information to increase personal knowledge and make business decisions. Allowed to access data but don't have time or the needed skills for analyzing Data in a higher structured manner. (Imhoff and White 2011; Eckerson 2014)	The most basic user with very limited skills. Allocated to every software as long as the focus of the software is not on high complicated tasks such as advanced analysis or data preparation.
Information Producer (power)	Power BI Users who gather information to increase personal knowledge and help to make tactical and strategic business decisions, who have time and the necessary skills for analyzing data and creating their own solutions. (Imhoff and White 2011; Eckerson 2014)	Each of the analyzed software tools address information producers. Therefore, the characteristic is assigned it to each software tool. However, the case study shows that there are also SSBIA application scenarios without information producers, namely when the IT provides an application in which information can be consumed.
Information Collaborator	They are specific subject matter experts and have the necessary skills to improve Data and Reports. They also rate existing Reports and give constructive criticism. (Imhoff and White 2011)	Allocated to the software if it has a strong emphasis on BI development collaboration and the possibility to write Comments on Reports.
User skills This Dimension describes the different technical skills and knowledge levels of business users. These skills include statistics, coding, data management, visualization and discovery and reporting technologies (Cosic et al. 2012). The more complex the SSBIA task and the accompanied SSBIA tool, the higher the required computer and analytical skills of business users need to be (Spahn et al. 2008; Eckerson 2014).		

Characteristic	Definition	Criteria for the assignment of the software
Basic	Users have low analytical, mathematical and IT skills and don't take part in implementation, architectural focus, or design oriented tasks. Their capabilities include "established views of data, routine queries, and regularly produced reports" (Imhoff and White 2011). (Eckerson 2014)	Allocated to the software if it has a very simple and manageable user interface and the software is mainly designed for simple applications such as drill down in reports.
Standard	Users have moderate mathematical and analytical skills, but low IT Skills (Eckerson 2014). "They are able to do ad hoc analysis as well as create and publish reports" (Imhoff and White 2011).	Allocated to the software if it has a simple user interface and the software is designed for uncomplicated creation (e.g. drag and drop) or editing of dashboard, reports, etc.
Advanced	Users have high analytical and mathematical skills, as well as moderate IT skills. They can include structured and unstructured Data in their self-created statistical analytics and reports, as well as predictive modeling and Data Mining (Imhoff and White 2011; Eckerson 2014). Data Scientists may also be covered if they do not fully implement the analysis in a programming language (Bani-Hani et al. 2019; Eckerson 2019).	Allocated to the software if it can be used for highly advanced analyses (e.g. k-means) and/or for complex data preparation/data processing. The analyses can be created or edited by coding.
BI analytics activities (based on Alpar and Schulz 2016) - **Hierarchical structure** BI analytics activities describes how SSBIA users use the data to be analyzed (Cosic et al. 2012). The dimension has a hierarchical structure. This means that the next level also contains the previous one. The dimension has a hierarchical structure which means that the following characteristic contains all underlying or previous characteristics.		
None	No BI analytic activities. Complete focus on data preparation can be a reason for it.	Allocated to the software if the theoretically possible applications of the software matched the characteristics definition.
Having access and using reports	Analyzing data by using reports.	Allocated to the software if the theoretically possible applications of the software matched the characteristics definition.
Report creation and data visualization	Creating new reports or accessing already existing reports, as well as visualizing and presentation of Data.	Allocated to the software if the theoretically possible applications of the software matched the characteristics definition.
Applying advanced analytics	Analyzing Data using advanced algorithms such as k-means or similar.	Allocated to the software if the theoretically possible applications of the software matched the characteristics definition.
Requirements for data management - Hierarchical structure This dimension describes the different demands of the respective SSBIA application scenarios with regard to data management. It is about the necessity to link different data sources, to connect new data sources, and to manipulate or cleanse the data (Cosic et al. 2012). The dimension has a hierarchical structure which means that the following characteristic contains all underlying or previous characteristics.		

Characteristic	Definition	Criteria for the assignment of the software
Only small changes	No complex data management necessary.	Allocated to the software if the theoretically possible applications of the software matched the characteristics definition.
Integration and modeling of existing data sources	Combination of different data sources. The creation of a new data model is necessary for this combination of data sources.	Allocated to the software if the theoretically possible applications of the software matched the characteristics definition.
Integration of new data sources	Adding new data source to existing or new reports. E.g. creation of complete ETL processes.	Allocated to the software if the theoretically possible applications of the software matched the characteristics definition.
Data cleansing and enhancing	Process of eliminating inconsistencies and errors in huge amount of data, and solving the object identity problem (Galhardas et al. 1999). This can include the adaption of data types or a combination and/or a separation of data fields.	Allocated to the software if the theoretically possible applications of the software matched the characteristics definition.
Collaboration in development - Hierarchical structure Distinguishes how strongly the cooperation of BI users is supported in a tool. This includes sharing and reusing of reports as well as social software features like rating or comments (Alpar et al. 2015). The dimension has a hierarchical structure which means that the following characteristic contains all underlying or previous characteristics.		
No software supported collaboration	No collaboration.	Allocated to the software if the theoretically possible applications of the software matched the characteristics definition.
Individualization of other people's reports	Possibility to use, adapt and further develop the reports of others (Alpar et al. 2015).	Allocated to the software if the theoretically possible applications of the software matched the characteristics definition.
Comments	Adding expert/domain knowledge through comments (Imhoff and White 2011; Alpar et al. 2015).	Allocated to the software if the theoretically possible applications of the software matched the characteristics definition.
Ratings	Improving data or reports of other users by rating figures or reports (Imhoff and White 2011).	Allocated to the software if the theoretically possible applications of the software matched the characteristics definition.
Access type - Hierarchical structure Describes how the reports can be accessed. Mobile devices require techniques for smaller displays and touch-capable control. Access via text interfaces is also conceivable (Power 2013; Tona & Carlsson 2013). The dimension has a hierarchical structure which means that the following characteristic contains all underlying or previous characteristics.		
Desktop	Access via a device like a notebook or desktop computer.	Allocated to the software if the technical capabilities of the software matched the characteristics definition.
Big Display (with touch)	Access via a device like a tablet or a big monitor (with or without touch control) in a conference room.	Not found in the analyzed sample.

Characteristic	Definition	Criteria for the assignment of the software
Mobile	Access via a device like a smartphone. (Tona and Carlsson 2013).	Allocated to the software if the technical capabilities of the software matched the characteristics definition.
Natural language	Access via a natural voice controlled device or a natural language chat. The device does not necessarily has a screen (Stedman 2017). The chat can include a chatbot.	Allocated to the software if the technical capabilities of the software matched the characteristics definition.
Nature of the analysis Describes what the main focus of the report / analysis is. Application scenarios can contain elements of all characteristics, but one characteristic is in the foreground (Schulz et al. 2015).		
No reporting	Tool includes process steps of an SSBIA analysis process, but has no component for reporting. E.g., it has no output of the data in the form of a dashboard or charts.	E.g., for tools that support the processing of data or the creation of an ETL process, but require an additional frontend for reporting.
Standard / scheduled	Reports are required several times in a similar form. Therefore, a high degree of automation for updating the data should be aimed at. The information is relevant at regular intervals (Schulz et al. 2015).	Allocated to the software if reports can be completely automatically generated, update timer can be used, etc. The high degree of automation is an outstanding characteristic of the software.
Ad-hoc	A one-time analysis is to be carried out. For this reason, the automation of data loading processes can be neglected. Initially, the focus is on a single use (Schulz et al. 2015).	Allocated to the software if reports, dashboards, etc. must be created or edited manually and are not automatically updated. Or if it's the dominant application scenario.
All-rounder	Includes one-time analysis as well as a high degree of automated report creation. Combination of the characteristics Standard/scheduled and Ad-hoc.	Allocated to the software if both of the previously mentioned characteristics are fulfilled, but neither of them is highlighted.
Data sensitivity / Privacy aspects Describes the "degree to which problems would arise if the contents of data files were known to others" (Zviran & Haga 1999, p.167). The degree is divided into five gradations.		
Non sensitive	No problems would arise if the data would be made public. There is "nothing to hide" (Zviran & Haga 1999, p.167).	Not analyzed.
Slightly sensitive	Minor problems would arise if the data would be made public.	Not analyzed.
Moderately sensitive	A few problems would arise if the data would be made public. It would be "mildly embarrassing" personally or for the organization (Zviran & Haga 1999, p.184).	Not analyzed.
Moderately high sensitive	Problems would arise if the data would be made public.	Not analyzed.
Highly sensitive	Major problems would arise if the data would be made public. It would be "embarrassing personally or to the organization" (Zviran & Haga 1999, p.184).	Not analyzed.

Characteristic	Definition	Criteria for the assignment of the software
Data reliability and completeness "Data reliability refers to the accuracy and completeness of computer-processed data, given the uses they are intended for" (Government Accountability Office, Applied Research and Methods: Assessing the Reliability of Computer-Processed Data (GAO-09-680G) (July 1, 2009). Whereas "Data completeness refers to the degree to which all data necessary for current and future business activities (e.g., decision making) are available in the firm's data repository" (Kwon et al. 2014 p. 389).		
Low	The selected data is not complete and/or reliable enough to solve the problem. Certain data is missing and/or needs to be adjusted first.	Not analyzed.
Medium	The selected data are almost complete and reliable for solving the problem, but some data still need to be added or adjusted.	Not analyzed.
High	The selected data is complete and reliable and allows to correctly solve the problem.	Not analyzed.

Databases used for finding SSBIA tools

Database	Gartner's Magic Quadrant Report	BI-Survey.com	Google	Own knowledge
Results	14	14	17	4
	Dropping of tools which do not fit our definition of SSBIA			
Final results	47 SSBIA tools			

List of analyzed SSBIA tools

Tool name	Company	Website
Allot ClearSee Analytics	Allot works	http://www.allotworks.com/ClearSee-Analytics.asp
Analyzer	Strategy companion	http://strategycompanion.com/
Birst	Birst Inc	https://www.birst.com/
Bissantz DeltaMaster	Bissantz	https://www.bissantz.com
BOARD	BOARD International	https://www.board.com/de
Cognos Analytics	IBM	https://www.ibm.com/de-de/products/cognos-analytics
Cubus outperform	Cubus	www.cubus.eu
Cyberquery	Cyberscience	www.cyberscience.com
Datapine self service analytics	Datapine	https://www.datapine.com/de/self-service-analytics
Diver platform	Dimensional insight	www.dimins.com/
Domo	Domo	www.domo.com
Einstein analytics	Salesforce	https://www.salesforce.com/de/products/einstein-analytics/overview/

Tool name	Company	Website
ElegantJ BI	ElegantJ BI	https://www.elegantjbi.com/smarten/self-serve-data-preparation.html
GoodData analytics platform	GoodData	https://www.gooddata.com/
Holistics	Holistics	https://www.holistics.io/product/data-reporting/
Ideata analytics	Ideata analytics	https://www.ideata-analytics.com/big-data-analytics/
Informer	Entrinsik	https://entrinsik.com/informer/
Intelligence portal	MarketLogic	https://www.marketlogicsoftware.com/intelligence-portal/
KNIME	KNIME	https://www.knime.com/
Logi vision	Logi analytics	https://www.logianalytics.com/
Looker	Looker	www.looker.com
Microsoft power BI	Microsoft	https://powerbi.microsoft.com
Microsoft power query for excel	Microsoft	https://www.microsoft.com/de-DE/download/details.aspx?id=39379
MicroStrategy 2019	MicroStrategy	https://www.microstrategy.com/us
Necto	Panorama	https://www.panorama.com/necto/
Oracle analytics cloud	Oracle	https://www.oracle.com/de/solutions/business-analytics/analytics-cloud.html#products
Paxata	Paxata	https://www.paxata.com/product/self-service-data-prep/
Phocas	Phocas	www.phocassoftware.com
Pyramid 2018	Pyramid analytics	https://www.pyramidanalytics.com/
Qlik Sense	Qlik	www.qlik.com
Rapidminer	Rapidminer	https://rapidminer.com/
SAP analytics cloud	SAP	https://www.sap.com/germany/products/cloud-analytics.html
SAP analysis for Microsoft office	SAP	https://help.sap.com/viewer/product/SAP_BUSINESSOBJECTS_ANALYSIS_OFFICE/2.8.3.0/en-US
SAP BusinessObjects web intelligence	SAP	https://www.sap.com/germany/products/bi-platform.html
SAS visual analytics	SAS	https://www.sas.com/de_de/software/visual-analytics.html
Sisense	Sisense	https://www.sisense.com/
Spotfire	TIBCO software	https://www.tibco.com/
SPSS modeler	IBM	https://www.ibm.com/de-de/products/spss-modeler/details
Tableau	Tableau	https://www.tableau.com/
Tamr	Tamr	https://www.tamr.com/supplier-analytics-2/
TARGIT decision suite	TARGIT	https://www.targit.com
ThoughtSpot	ThoughtSpot	https://www.thoughtspot.com/de
WebFOCUS	Information builders	https://www.informationbuilders.com/

Tool name	Company	Website
Workday prism analytics	Workday	https://www.workday.com/de-de/applications/prism-analytics.html
Wrangler	Trifacta	https://www.trifacta.com/
Yellowfin BI	Yellowfin	www.yellowfinbi.com
Zoomdata	Zoomdata	https://www.zoomdata.com/product/self-service-bi-analytics/

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Data availability Can be found in the Appendix.

Code availability Not applicable.

Declarations

Conflict of interest The authors have no conflicts of interest to declare that are relevant to the content of this article.

References

Abelló A, Darmont J, Etcheverry L, Golfarelli M, Mazón JN, Naumann F, Vossen G (2013) Fusion cubes: towards self-service business intelligence. Int J Data Warehouse Min 9(2):66–88

Alpar P, Schulz M (2016) Self-service business intelligence. Bus Inf Syst Eng 58(2):151–155

Alpar P, Engler TH, Schulz M (2015) Influence of social software features on the reuse of business intelligence reports. Inf Process Manag 51(3):235–251

Balijepally V, Mangalaraj G, Iyengar K (2011) Are we wielding this hammer correctly? A reflective review of the application of cluster analysis in information systems research. J Assoc Inf Syst 12(5):375–413

Bani-Hani I, Tona O, Carlsson S (2018a) From an information consumer to an information author: a new approach to business intelligence. J Organ Comput Electron Commer 28(2):157–171

Bani-Hani I, Pareigis J, Tona O, Carlsson S (2018b) A holistic view of value generation process in a SSBI environment: a service dominant logic perspective. J Decis Syst 27(1):46–55

Bani-Hani I, Deniz S, Carlsson S (2017) Enabling organizational agility through self-service business intelligence: the case of a digital marketplace. In: Proceedings of the 21st Pacific Asia Conference on Information Systems.

Bani-Hani I, Tona O, Carlsson S (2019) Modes of engagement in SSBA: a service dominant logic perspective. In: Proceedings of Americas Conference on Information Systems. Association for Information Systems.

Benyon D (2014) Designing interactive systems: a comprehensive guide to HCI, UX and interaction design. Pearson Education, London, United Kingdom
Berthold H, Rösch P, Zöller S, Wortmann F, Carenini A, CampbellS, Strohmaier F (2010) An architecture for ad-hoc and collaborative business intelligence. In: Proceedings of EDBT/ICDT Workshops
Böhringer M, Gluchowski P, Kurze C, Schieder C (2009) On the role of social software techniques for the design of self-organising enterprise reporting portals. In: Proceedings of International Conference on Information Technology Interfaces. pp 153–158
Burke M, Simpson W, Staples S (2016) The cure for ailing self-service business intelligence. Bus Intell J 21(3)
Burnay C, Gillain J, Jureta IJ, Faulkner S (2014) On the definition of self-service systems. In: Proceedings of International Conference on Conceptual Modeling. Springer, Cham, pp 107–116
Business Application Research Center (BARC) (2022). Data, BI & Analytics Trend Monitor 2022. https://barc.de/Artikel/infografik-data-bi-analytics-trend-monitor-2022. Accessed at 17 July 2022
Chen H, Chiang RH, Storey VC (2012) Business intelligence and analytics: from big data to big impact. MIS Q 36(4):1165–1188
Clarke P, Tyrrell G, Nagle T (2016) Governing self service analytics. J Decis Syst 25(1):145–159
Convertino G, Echenique A (2017) Self-service data preparation and analysis by business users: new needs, skills, and tools. In: Proceedings of Conference Extended Abstracts on Human Factors in Computing Systems, pp 1075–1083
Corral K, Schuff D, Schymik G, St Louis R (2015). Enabling self-service bi through a dimensional model management warehouse. In: Proceedings of Americas Conference on Information Systems.
Cosic R, Shanks G, Maynard S (2012) Towards a business analytics capability maturity model. In: Proceedings of Australasian Conference on Information Systems
Daradkeh MK (2019) Determinants of visual analytics adoption in organizations. Inf Technol People Int J Inf Syst Serv Sect 11(1):68–89
De Mauro A, Greco M, Grimaldi M, Ritala P (2018) Human resources for Big Data professions: a systematic classification of job roles and required skill sets. Inf Process Manag 54(5):807–817. https://doi.org/10.1016/j.ipm.2017.05.004
Eckerson WW (2009) Self-service BI. TDWI Checklist Report, TDWI Research. https://tdwi.org/research/2009/07/self-service-bi.aspx. Accessed 24 Sept 2020
Eckerson W (2011) Analytic architectures: approaches to supporting analytics users and workloads. BeyeRESEARCH. https://www.bitpipe.com/detail/RES/1300999636_711.html. Accessed 24 Sept 2020
Eckerson WW (2012) Business-driven BI: Using new technologies to foster self-service access to insights. Tableau Software. https://www.tableau.com/learn/whitepapers/business-driven-bi. Accessed 24 Sept 2020
Eckerson WW (2014) Five steps for delivering self-service business intelligence to everyone. Information Builders. https://fst.net.au/wp-content/uploads/file/whitepaper/5_steps_to_self-service_bi.pdf. Accessed 24 Sept 2020
Eckerson WW (2019) How to succeed with self-service analytics. https://www.eckerson.com/articles/succeeding-with-self-service-analytics-know-thy-customer. Accessed 24 Sept 2020
Galhardas H, Florescu D, Shasha D, Simon E (1999) An extensible framework for data cleaning. Institute National de Recherche en Informatique ét en Automatique, Technical Report. https://hal.inria.fr/inria-00072922. Accessed 24 Sept 2020
Gartner (2018) Gartner says self-service analytics and BI users will produce more analysis than data scientists will by 2019. https://www.gartner.com/en/newsroom/press-releases/2018-01-25-gartner-says-self-service-analytics-and-bi-users-will-produce-more-analysis-than-data-scientists-will-by-2019. Accessed 24 Sept 2020
Gimpel H, Rau D, Röglinger M (2018) Understanding FinTech start-ups–a taxonomy of consumer-oriented service offerings. Electron Mark 28(3):245–264
Glass RL, Vessey I (1995) Contemporary application-domain taxonomies. IEEE Softw 12(4):63–76
Goeken M, Mayer JH, Bork Z, Quick R (2014) App design for use—a manager perspective for in-memory technology. In: Proceedings of Conference on Business Informatics, pp 110–118
Halper F (2017) TDWI self-service analytics maturity model guide. https://www.microstrategy.com/Strategy/media/downloads/white-papers/TDWI-Self-Service-Maturity-Model-Guide.pdf. Accessed 24 Sept 2020

Hevner AR, March ST, Park J, Ram S (2004) Design science in information systems research. MIS Q 28(1):75–105
Horvath MM, Rusincovitch SA, Brinson S, Shang HC, Evans S, Ferranti JM (2014) Modular design, application architecture, and usage of a self-service model for enterprise data delivery: the duke enterprise data unified content explorer (DEDUCE). J Biomed Inform 52:231–242
Howson C (2015) Embrace self-service data preparation tools for agility, but govern to avoid data chaos. Gartner.
Imhoff C, White C (2011) Self-service business intelligence. Empowering users to generate insights. TDWI Best practices report, TWDI, Renton, WA.
Janssen A, Passlick J, Rodríguez Cardona D, Breitner MH (2020) Virtual assistance in any context—a taxonomy of design elements for domain-specific chatbots. Bus Inf Syst Eng 62(3):211–225
Johannessen TV, Fuglseth AM (2016) Challenges of self-service business intelligence. Norsk konferanse for organisasjoners bruk at IT, 24(1)
Johansson B, Alkan D, Carlsson R (2015) Self-service BI does it change the rule of the game for BI systems designers. In: Proceedings of BIR Workshops, pp 48–61
Kobielus J, Karel R, Evelson B, Coit C (2009) Mighty mashups: do-it-yourself business intelligence for the new economy. Forrester Research
Kosambia S (2008) Business intelligence the self-service way. Inf Manag 18(7):20
Kretzer M, Kleinedler M, Theilemann C, Mädche A (2015a) Designing a report recommendation assistant: a first design cycle. In: Proceedings of International Conference on Design Science Research in Information Systems, Springer, Cham, pp 87–103
Kretzer M, Gaß O, Mädche A (2015b) Design principles for diffusion of reports and innovative use of business intelligence platforms. In: Proceedings der 12. Internationalen Tagung Wirtschaftsinformatik, pp 675–690
Lennerholt C, van Laere J (2019) Data access and data quality challenges of self-service business intelligence. In: Proceedings of European Conference on Information Systems
Lennerholt C, van Laere J, Söderström E (2018) Implementation challenges of self service business intelligence: a literature review. In: Proceedings of Hawaii International Conference on System Sciences.
Li Y, Thomas MA, Osei-Bryson KM (2017) Ontology-based data mining model management for self-service knowledge discovery. Inf Syst Front 19(4):925–943
Liu L, Kim K, Sun W (2012) An empirical research of factors affecting collaborative decision making system. Int J Hybrid Inf Technol 5(4):1–10
Mayer JH, Röder A, Hartwig J, Quick R (2014) A self-service MSS design from a new-generation manager perspective. In: Proceedings of International Conference on Design Science Research in Information Systems, Springer, Cham, pp 164–179
Meyers C (2014) How data management and governance can enable successful self-service BI. TDWI Bus Intell J 19(4):23–27
Michalczyk S, Nadj M, Azarfar D, Maedche A, Gröger C (2020) A state-of-the-art overview and future research avenues of self-service business intelligence and analytics. In: Proceedings of European Conference on Information Systems
Michalczyk S, Nadj M, Maedche A, Gröger C (2021) Demystifying job roles in data science: a text mining approach. In: Proceeding of the European Conference on Information Systems
Miller JG, Roth AV (1994) A taxonomy of manufacturing strategies. Manag Sci 40(3):285–304
Moore S (2017) Gartner says more than 40 percent of data science tasks will be automated by 2020. https://www.gartner.com/newsroom/id/3570917. Accessed 01 Feb 2022
Morton K, Balazinska M, Grossman D, Mackinlay J (2014) Support the data enthusiast: challenges for next-generation data-analysis systems. Proc VLDB Endow 7(6):453–456
Mullarkey MT, Hevner AR, Gill TG, Dutta K (2019) Citizen data scientist: a design science research method for the conduct of data science projects. In: Proceedings of the International Conference on Design Science Research in Information Systems and Technology. Worcester, MA, USA, June 4–6, Springer, Cham, pp 191–205
Naish AG (2013) Cloud based self service analytics. In: Proceedings of ISI World Statistic Congress, 25–30 August 2013, Hong Kong (Session CP), pp 4816–4820
Nickerson RC, Varshney U, Muntermann J (2013) A method for taxonomy development and its application in information systems. Eur J Inf Syst 22(3):336–359
Ogushi Y, Schulz M (2016) Self-service business intelligence (SSBI): Categorizing into dimensions of interest in scholarly literature. 新潟大学経済論集, 100:97–115

Passlick J, Guhr N, Lebek B, Breitner MH (2020) Encouraging the use of self-service business intelligence–an examination of employee-related influencing factors. J Decis Syst 29(1):1–26
Passlick J, Lebek B, Breitner MH (2017) A self-service supporting business intelligence and big data analytics architecture. In: Proceedings of Internationale Tagung Wirtschaftsinformatik.
Pickering C, Gupta M (2015) Self service business intelligence (SSBI) for employee communications and collaboration (ECC). In: International Conference on Collaboration Technologies and Systems, pp 302–304
Poonnawat W, Lehmann P (2014) Using self-service business intelligence for learning decision making with business simulation games. CSEDU 2:235–240
Power DJ (2013) Mobile decision support and business intelligence: an overview. J Decis Syst 22(1):4–9. https://doi.org/10.1080/12460125.2012.760267
Savinov A (2014) Concept mix-self-service analytical data integration based on the concept-oriented model. In: DATA, pp 78–84
Schlesinger PA, Rahman N (2016) Self-service business intelligence resulting in disruptive technology. J Comput Inf Syst 56(1):11–21
Schuff D, Corral K, Louis RDS, Schymik G (2018) Enabling self-service BI: a methodology and a case study for a model management warehouse. Inf Syst Front 20(2):275–288
Schulz M, Winter P, Choi S-KT (2015) On the relevance of reports—integrating an automated archiving component into a business intelligence system. Int J Inf Manage 35(6):662–667
Smuts M, Scholtz B, Calitz A (2015). Design guidelines for business intelligence tools for novice users. In: Proceedings of Annual Research Conference on South African Institute of Computer Scientists and Information Technologists.
Sokal RR, Michener CD (1958) A statistical method for evaluating systematic relationships. Univ Kansas Bull 38(2):1409–1438
Spahn M, Kleb J, Grimm S, Scheidl S (2008) Supporting business intelligence by providing ontology-based end-user information self-service. In: Proceedings of international workshop on Ontology-supported business intelligence.
Stedman C (2017) Barbecue chain eyes using Alexa to augment BI dashboards in kitchens. https://searchbusinessanalytics.techtarget.com/feature/Barbecue-chain-eyes-Alexa-to-augment-BI-dashboards-in-kitchens?src=5683488&asrc=EM_ERU_84571893&utm_content=control&utm_medium=EM&utm_source=ERU&utm_campaign=20171027_ERU%20Transmission%20for%2010/27/2017%20(UserUniverse:%202461005). Retrieved 17 Jan 2021
Stodder D (2015) Visual analytics for making smarter decisions faster–applying self-service business intelligence technologies to data-driven objectives. TDWI Best Practices Report. TDWI Research
Stone MD, Woodcock ND (2014) Interactive, direct and digital marketing. J Res Interact Mark 8(1):4–17
Sulaiman S, Gómez JM, Kurzhöfer J (2013) Business intelligence systems optimization to enable better self-service business users. In: Proceedings of Workshop of Business Intelligence, pp 35–46
Szopinski D, Schoormann T, Kundisch D (2019) Because your taxonomy is worth it: towards a framework for taxonomy evaluation. In: Proceedings of European Conference on Information Systems. Stockholm
Tavera Romero CA, Ortiz JH, Khalaf OI, Ríos Prado A (2021). Business intelligence: business evolution after industry 4.0. Sustainability 13(18)
Tona O, Carlsson SA (2013) The organizing vision of mobile business intelligence. In: Proceedings of the European Conference on Information Systems.
Vance A, Lowry PB, Eggett DL (2015) Increasing accountability through the user interface design artifacts: a new approach to addressing the problem of access-policy violations. MIS Q 39(2):345–366
Varga J, Romero O, Pedersen TB, Thomsen C (2014). Towards next generation BI systems: the analytical metadata challenge. In: Proceedings of International conference on data warehousing and knowledge discovery, Springer, Cham, pp 89–101
Varshney U, Nickerson R, Muntermann J (2015) Towards the development of a taxonomic theory. In: Proceedings of the American Conference of Information Systems
Vom Brocke J, Simons A, Riemer K, Niehaves B, Plattfaut R, Cleven A (2015) Standing on the shoulders of giants: challenges and recommendations of literature search in information systems research. Commun Assoc Inf Syst 37(9):205–224
Ward JH (1963) Hierarchical grouping to optimize an objective function. J Am Stat Assoc 58(301):236–244
Weber M (2013) Keys to sustainable self-service business intelligence. Bus Intell J 18(1):18–24

Webster J, Watson RT (2002) Analyzing the past to prepare for the future: writing a literature review. MIS Q 26(2):13–23
Weiler S, Matt C, Hess T (2019). Understanding user uncertainty during the implementation of self-service business intelligence: a thematic analysis. In: Proceedings of Hawaii International Conference on System Sciences
Yin RK (2009) Case study research: design and methods, vol 4. Sage, Los Angeles
Yu E, Lapouchnian A, Deng S (2013) Adapting to uncertain and evolving enterprise requirements: the case of business-driven business intelligence. In: Proceedings of International Conference on Research Challenges in Information Science. IEEE.
Zaghloul MM, Ali-Eldin A, Salem M (2013) Towards a self-service data analytics framework. Int J Comput Appl 80(9):41–48
Zilli D (2014) Self-service business intelligence for higher education management. In: Proceedings of the International Conference on Management, Knowledge and Learning. Portoroź, Slovenia.
Zorrilla M, García-Saiz D (2013) A service oriented architecture to provide data mining services for non-expert data miners. Decis Support Syst 55(1):399–411

Authors and Affiliations

Jens Passlick[1] · **Lukas Grützner**[1] · **Michael Schulz**[2] · **Michael H. Breitner**[1]

Lukas Grützner
gruetzner@iwi.uni-hannover.de

Michael Schulz
michael.schulz@nordakademie.de

Michael H. Breitner
breitner@iwi.uni-hannover.de

1 Information Systems and Management Institute, Leibniz Universität Hannover, Königsworther Platz 1, 30167 Hannover, Germany

2 Nordakademie, Elmshorn, Germany