Modes of Engagement in SSBA: a Service Dominant Logic Perspective

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Abstract

The main premise of self-service business analytics (SSBA) is to make business users autonomous during data analytics. Driven by this potential, organizations are spending resources to design SSBA environmet to empower business employees and decentralize the analytics capabilities. Yet, little is known about how SSBA is facilitating business employees' independence, and moreover, the value that is co-created. Based on empirical data from a major Norwegian online marketplace and drawing on service-dominant logic as an analytical framework, we identify three main modes of data engagement in SSBA: no dependency, high dependency, and low dependency. Furthermore, we identify the required business users' resources in the analytical processes in each mode. We discuss the organizational implications of these findings.

Keywords

Resource integration, interaction, self-service business analytics, service dominant logic.

Introduction

Data-driven organizations, such as Google and Amazon, are at the forefront of data analytics capabilities (McAfee et al. 2012). In similar vein, many other organizations are investing capital in cutting-edge technologies and services in order to be able to make fact-based decisions just in time. Unsurprisingly, the field of data analytics (that includes business intelligence, business analytics, and big data) has attracted wide attention from both an industry and academic standpoint (Chen et al. 2012). Business intelligence (Kowalczyk et al. 2013; Popovič et al. 2012) or business analytics (BA), often used interchangeably, represents "a broad category of applications, technologies and processes for gathering, storing, accessing and analyzing data to help business users make better decisions" (Watson 2009,p. 491). BA has expanded across different levels in organizations encompassing both the managerial and the operational level (Böhringer et al. 2010). This outreach is largely driven by the dynamic environment where demands for updated reports and information, either standard or ad hoc, are dramatically increasing (Yu et al. 2013). Given this flood of requests and resource limitations, such as availability of BI analysts, the process of delivering the right information in time is obstructed (Kobielus et al. 2009). Subsequently, in the absence of timely information, decision-makers may feel forced to act without consulting all available data (Abelló et al. 2013).

Against this drawback, a new promising approach to BA — coined self-service business analytics (SSBA) — aims to decrease the level of employees' dependency while engaging with a broad range of applications and tools comprehensively embedded throughout the process of solving an analytical task (Bani-Hani et al. 2018). SSBA enables business users to not only access data but also build customized reports based on their needs (Weber 2013). Thus, data analytical capability extends beyond BI analysts and data scientists (referred to as techno-oriented users in this paper). Other business employees from a variety of departments, such as sales and marketing, are empowered to exploit data in order to draw conclusions and make business decisions (Imhoff and White 2011). Thus, SSBA has the potential to shift business employees' role from a data consumer to also an information producer (Bani-Hani et al. 2018). SSBA approach is not trivial, and it carries challenges that may be crucial to its success. Business employees and techno-oriented employees should collaborate during data source selection, the semantic layer of the data, data fields, and creation of a data model (Imhoff and White 2011). Because of a wide variety of business users' expertise and experience, the process may be complex and 'a one-size fits all' may jeopardize the value of SSBA.

Little is known about how SSBA is facilitating business users' independence, considering that a lack of adequate experience and expertise may result in wrong data selection and consequently risking the effectiveness of the analytical process. Hence, legitimate concerns that arise are: how can these cases be prevented, what are the necessary skills and knowledge that employees should have in order to engage in an SSBA, or how should collaboration and communication be configured among business users and techno-oriented users when using different tools and processes to independently analyze data? Indeed, these questions center on maximizing the value that is generated in an SSBA. Given the above, the aim of this paper is to identify the optimal level of dependency in SSBA and particularly its enablers. To fulfill this aim, we investigate the ways in which employees (i.e., business employees and techno-oriented employees) integrate their resources in SSBA during an analytical task. This paper evaluates three dependency levels and provides valuable insights and suggestions to organizations planning to or have already invested in becoming data-driven by adopting an SSBA approach. Through a service-dominant logic (SDL) perspective (Vargo and Lusch 2008; Vargo and Lusch 2016b) at a micro-level, (i.e., intra-organizational) we apply a multidisciplinary, dynamic, and evolving narrative of value co-creation through resource integration and service exchange.

Self-Service Business Analytics from a User Perspective

The large amount of data (volume) and the wide range of data types (variety) being generated and captured at high speed (velocity) (Russom 2011) are influencing the decision-making landscape in organizations (Beynon et al. 2002). Making right decisions on time is crucial for an organization's survival and its competitive advantage. As a technological solution, SSBA enables the capability of business users at different levels to independently build custom reports and explore previous ones without relying on the IT/BI department (Abbasi et al. 2016). This enhanced capability plays an important role in augmenting the organizational agility to respond to a rapidly changing business (Bani Hani et al. 2017; Park et al. 2017). The main premise of SSBA is to provide independence to business employees. In other words, business employees should be able to solve an analytical task without the support of the IT/BI department. From a technological perspective BA users are categorized into three main groups (Phillips-Wren and Hoskisson 2015):

- Business users, often known as casual users, use applications without being aware of the complex analytical processing involved. They have basic technical skills and domain-based expertise.
- Business analysts have extensive analytical skills compared to those of business users. They can analyse data, understand how data is organized, retrieve data via ad hoc queries, produce specialized reports, and build what-if scenarios. They often produce information requested by business users.
- Data scientists have a strong background in mathematics, statistics, and/or computer science. Therefore, they are able to develop descriptive, predictive, and prescriptive models (perhaps using the discovery platform; e.g., Sandbox), evaluate models, deploy, and test them through controlled experiments.

The focus of the SSBA approach is to empower the first category of users (i.e., business users). Therefore, in this paper, we streamline the above categorization by grouping users into business users and techno-oriented users. Business users are mainly operational employees (such as field and operational staff, sales-people, and executives/managers) in need of information during their everyday work, and they have little specialization on data analytics. Whereas techno-oriented users are employees whose job description is strongly connected to data analytics, programming skills, intimate knowledge about data sources, and semantic meanings.

Value Co-creation in Service-Dominant Logic

SDL — sometimes referred to as philosophical foundation for service science (Maglio and Spohrer 2008)— is frequently applied in the IS discipline. For example, it has been used to study service-oriented architecture (SOA) (Yan et al. 2010), to design a framework of service innovation (Lusch and Nambisan 2015b), and to develop new business models as a way of generating value from big data (Chen et al. 2017). Service is at the core of SDL. Historically, services have been assumed to be different from goods. Unsurprisingly, goods-related industries, such as agriculture, mining, and automotive, have been categorized as extractive and manufacturing industries. Whereas service-related industries, such as health care and entertainment, have been categorized as industries with a focus on non-physical goods (i.e., non-tangible offerings). Nowadays, researchers are investigating service delivery through a new lens. SDL — initially proposed as a new dominant logic for the marketing field (Vargo and Lusch 2004)— represents a meta-theoretical framework to explain value co-creation through resource integration and service exchange in a network of actors. The fundamental notion of SDL is that actors apply their competences (resources) to benefit others and equally benefit from others' applied competences within service-for-service exchange (Vargo and Lusch, 2004).

Resource integration is “the process by which customers deploy [...] resources as they undertake bundles of activities that create value directly or that will facilitate subsequent consumption/use from which they derive value” (Hibbert et al. 2012, p. 2). However, the notion of customer-producer dyad in this definition is challenged, and it is further generalized to actor-to-actor networks (Vargo and Lusch 2016b). Resource integration is tightly linked to service exchange and thereby difficult to separate because in resource integration actors engage in a mutual service provision, or in other words service exchange (Vargo and Lusch 2011). Resource integration happens for two main reasons: first, to generate value or usefulness when resources obtained by an actor are combined or bundled with other resources (Lusch and Nambisan 2015b), and second, to encourage innovation through recombination of existing resources (Arthur 2009).

Institutions and institutional arrangements are essential during resource integration and service exchange. Institutions encompass actors, norms, rules, beliefs, and general mind-set that drives actors’ actions (Vargo and Lusch 2016a) (inline with the institutional logic where it provides description on institutions at individual and organizational level). When actors share the same norms, beliefs, and mind-set, a network effect is created that, in turn, enables a more productive encouraging value co-creation (Vargo and Lusch 2016a). Value co-creation is defined as the process or patterns within an activity that is enabled by actors’ resource integration and service exchange controlled by institutions (Lusch and Nambisan 2015a). In a service ecosystem, under the control of institutions, actors co-create value through integrating resources, such as experience, cognitive skills, technical skills, and time to exchange services with one-another. In an SSBA, service exchange happens when a business employee initiates an analytical task within a pre-configured environment driven by data, technology, and analytics. Through SDL, in this paper we seek to explain how different actors integrate their resources and exchange services to co-create the desired value in a process driven by institutions and arrangements. Due to different institutions (norms, mind-set, etc.) in an SSBA, we expect different actor configurations during resource exchanges that aim to co-create value.

Research Method

This paper adopts a single case study (Hayes et al. 1999) especially. Through qualitative interviews, we provide rich descriptions (Schultze and Avital 2011) and insights to investigate how value is co-created when business users engage with tools, applications, and other techno-oriented employees to solve analytical tasks. To meet the aim of this study, we chose an organization that fulfilled two main selection criteria: (a) service-oriented organization, and (b) has already implemented tools and applications to set-up and facilitate an SSBA for its employees. Regarding the former, we believe that service-oriented organizations depend on data to highly perform; whereas for the latter, it is necessary to observe the phenomena of this study in an organization that is devoting time and money to SSBA.

Empirical Case

Finn.no, a top digital marketplace in Norway, met both of our selection criteria. Parties such as buyers, sellers, and market intermediaries use Finn.no's digital platform and services to carry out business transactions and activities. Finn.no has become a central data repository where agencies (private and public) constantly send requests that consist of various statistical analysis and ad hoc reports. In addition, high profile sellers are requesting reports from departments of marketing and sales about their advertisement reach and thereby investments value. Due to an increase in ad hoc requests from external customers and internal employees, in 2010, Finn.no management decided to invest to become a more data-driven organization, where employees could easily access and analyze business data to perform their daily tasks more independently. For this purpose, the organization adopted an SSBA approach, which could (hopefully) augment employees' capabilities to handle not only external customers' requests in time, but also their personal needs for timely information. The IT department is responsible for the maintenance of SSBA tools, applications, and platform in general. The IT staff creates data models, modifies data models, and manages user access throughout the platform. Often, the IT staff interacts with other employees in case of assistance, training, or any needed modifications in the data models. Finn.no aims to empower employees to create reports and dashboards through accessing the data warehouse, combining several data sources data (creating mashups), and exporting previous reports to other formats (such as Power Point and Excel).

There are two sources of evidence in this study: semi-structured interviews and organizational surveys with employees and internal documents such as data sources, tools and techniques for data analysis. The semi-structured interviews took place at Finn.no between February and May 2016, in Oslo, Norway. This data point contained thirteen face-to-face semi structured interviews with a total of 14 hours and 30 min. The interview guide was developed based on SDL's main components and questions in relation to resource integration in SSBA (e.g. based on what do you select from the data source?), service exchange nature (e.g. what do you gain from engaging with data by yourself and how does that affect the technical department?) and institutions within the organization (what it means to be data driven and how it is aligned with the organization vision). By doing so, we have created three main themes that provided a focused investigation of the phenomenon with an SDL lens. The second data point was an internal survey carried out by the technical department consisting of 26 interviews with product developers, managers and c-level employees to record the current employees technical skills in relation to the analytical problem solving process shown in **Table 1**.

Data Analysis

All interviews were recorded, transcribed, and loaded into NVIVO11 with the consent of the interviewees. Our analysis employed two levels of coding schema etic and emic introduced by Miles and Huberman (1994. The first level of coding (etic) was built on the S-D logic lens presented in section three. We first created nodes in NVIVO11 corresponding to the main elements of the value co-creation, which is actors, resource integration, service exchange, institution, and service ecosystem to serve as ground categories. At the second level of coding (emic) codes were generated incrementally during data analyses (Miles and Huberman 1994). For instance, in resource integration, codes that emerged included: "technical resource", "support", "setup", and "engagement".

Findings

The findings of this study are structured based on the value co-creation process of SDL (Vargo and Lusch 2016b). Based on the context of this study, the main actors involved in an SSBA are the employees who engage in daily analytical tasks (business users) and the techno-oriented people who support them. Most of the techno-oriented employees are part of the IT/BI department, whereas business users work in other operational departments, such as product development, sales, marketing, and public relations. Our secondary data provides insights into the main processes involved during an analytical task, and as shown in **Table 1**, it highlights the needed capabilities of employees to engage in each process.

Institutions

In this study, institutions provide foundations for a data-driven mind-set, whereas institutional arrangements entail the way employees share the same ideology and the way they communicate and engage in SSBA. In this study we describe two types of institution; individual and organizational institutions. From an organizational institutional perspective Finn.no is designing strategies to become data-driven: *"Our organization had just concluded a strategy… the main pillar of that strategy was to become a more data-driven organization." (CFO)*. Interestingly, before this new strategy, employees were proactively becoming independent from the IT/BI department to efficiently fulfill their daily needs. This is especially important for new employees as the alignment between their personal institutions and the organization institutions is crucial for sustaining an SSBA. *"When I joined Finn, I would say that in a lot of places, there were some pockets (small groups) of people who had started to create mini data-models [because they] needed to be more responsive in their daily needs of data." (CFO)*. Given this initiative from a small group of employees and the organization's strategy, higher management decided to promote fact-based decision-makings among all employees by formally introducing new technologies (e.g., big screens visualizing real-time KPI and self-service BI tools), processes to support business employees in data analytics. This strategy helps in supporting existing institutions and developing new ones. That is, organizations should design the organization to nurture needed institutions, such as data driven and fact-based decision-making. *"The key thing that we are doing is trying to make existing structured data available, such that more users within Finn can retrieve data so that they can analyze the data themselves…What we essentially said in our organization is that we want data to be a part of our instinct." (CFO) ,"…what then happened is that some people in other companies, they started to hear about our new tool, then they came to us and asked for it." (CFO)*. Some employees perceive these transformations in the organization as 'core changes' that enable them to work independently with data. *"I think the change is in the way that I used to do things, the change is that I look at what I am supposed to do everyday in numbers and I answer questions with facts without relying on the insight department, so it is like having data in our spine." (Business user)*

Process	Capabilities
Data gathering	-Data source access (e.g. Identify sources, make some source quality assessments,) -Data source comprehension (e.g. Ability to use secondary sources in context) -Data source manipulation (e.g. Create data source, Make critical selection of sources -Data source mashup (e.g. Combine data sources based on quality vs. use-case,)
Data preparation	-Data processing (e.g. use pre-made calculations,) -Data cleaning (e.g. Correct missing/skewed data,) -Data adjustment (e.g. Outlier handling, Indexing, Define measures/dimensions…) -Data integration (e.g. Cross source calculation, Can use any tool according to objective, …)
Analysis	-Analytical preparation (e.g. open excel and look at tables) -Basic analysis (e.g. Sum, grouping, average,) -Descriptive analysis (e.g. Median/percentile, Descriptive, Filtering, Outlier handling, Elementary A/B testing,) -Statistical model analysis (e.g. Standard deviation , Variance, Regression, Know A/B, testing boundaries, Test=hypothesis,)
Visualization	-Insight presentation (e.g. copy from excel to PPT) -Export to different formats (e.g. more advanced PPT/PDF from multiple sources) -Create visualization (e.g. visualization published on tableau server, Create reports in adobe,) -Create dashboards (e.g. Visualization published on tableau server, Create reports in adobe,) -Create ad-hoc visualization (e.g. Create dashboard in tableau, Share ad-hoc reports in adobe,)
Interpretation	-Using ready reports and analysis (e.g. Navigate basic system, use information provided to address a task)

Table 1: Analytical problem-solving capabilities in SSBA

Resource Integration and Service Exchange

Tangible and intangible resources (Lusch and Vargo 2014) are being used by employees during the analytical processes. In this study, techno-oriented and business employees integrate intangible resources (such as knowledge of the best data sources for the task at hand, business understanding and previous experience) and tangible (such as the ability to use different tools such as PPT, creating dashboards and visualizations). For a successful resource integration and service exchange in an SSBA, tools and data provided for employees should be in line with their requirements and business needs. During data engagement, business employees integrate their personal resources with the available resources in the SSBA to answer an analytical question. We identify three modes of engagement characterized by the level of dependency between business employees and techno-oriented employees. These modes are: no dependency, low dependency and. high dependency.

Mode A (No Dependency): In the 'no dependency' mode, business employees are involved independently in gathering data from different sources, data preparation, data analysis, build visual representation of the processed data and interpret the results to generate insights (i.e., without the support of techno-oriented users). By integrating their resources, namely business knowledge, and relevant technical skills (see Table 1) with the available resources of the SSBA, business users are able to process data and generate insights. Often business employees engage through the whole processes of data analyses because of personal reasons. Hence, enable creating reports that meet their needs. *"I sometimes use Tableau to look into the data that decides my commission. As I understand the business, I use my personal time and build reports by myself. I organize my sales data in a specific format to see if I am missing commission. So, it was like you can earn 10,000 more if you spent like 3 days a month and trust the report you created." (business user).* In other more complex tasks, business employees may need to design other types of reports that allow more analytical interpretation, such as categorizing customers based on business segments and activities, or testing new hypotheses. *"I use Tableau [one of the self-service tools available] and build reports based on customer data and business segments that show me how many impressions [i.e., views] per search on our platform… so, it helps me sell our services by showing how customers are doing." (business user), "I use self-service to see how many save ads and how many have saved searches on this topic. For instance, we have some hypotheses that if we just put a link to a page on the first page in a specific location then we can address more people and then after a certain time, I just go into self-service and see if we are getting more people to look at the link by this change." (business user)*

To be able to design these types of reports, business users must have good technical skills such as Statistical model analysis, the ability to create visualization and dashboards, etc. (see **Table 1**) and be able to perform analytical interpretation of the findings based on their business knowledge the employees also must possess certain capabilities (see **Table 1**). *"I have good technical experience in Tableau so I have created some customer reports based on my business understanding [and placed them] on my desktop using the desktop version of Tableau [one of the self-service tools,] so I have a lot of the data needed available locally on my machine. I can easily extract very quickly all the data on my machine and all the tables and formatting the way I want so that I can easily analyse it and [feel] confident that I will generate insights." (business user)* Complex analytical tasks often require business employees to engage in data gathering by identifying the different data sources, access them and make some data quality assessments. Then extract data using different tools, and integrate the needed data into one tool to be able analyse the data using different analytical techniques (see **Table 1**), visualise it hence interpret to insights. *"So I need to go and make an extract from Tableau and an extract from CRM system and then match that data to get the industry and size of the company … so I pull data from different sources and put them into Excel … it is easier in Excel.. I know Excel is not the best BI visualization tool but it's good for some stuff." (business user), "Excel, Adobe, Tableau and then I sometimes use different tools to scrape website [data] in order to get data structures of competitors" (business user)*

Mode B (Low Dependency): In 'low dependency', business employees are involved independently in data analysis, build visual representation of the processed data and interpret the results to generate insights (i.e., with partial support of techno-oriented users). In other words, business employees deliver the final results after they have integrated their resources and capabilities such as analytical preparation, Create dashboards, Create ad-hoc visualization, etc. (see **Table 1**) with those of techno-oriented users at some point in the process. In this mode of engagement, business employees lack knowledge on how to access, gather, and prepare for later stages (first two processes in table 1). This entails that business employee rely on techno-oriented people to prepare and optimized data models in order to perform data analysis, visualization and finally interpretation. Employees, in this mode of engagement, have low dependency and need limited support since the involvement of techno-oriented user involvement does not exceed 30% of the whole process. When asking a business development employee about the nature of support and assistance techno-oriented people provide: *"One would be just getting help extracting or manipulating the data or just getting the tie (connection) to do it."* The reason for this needed support is the lack of precise knowledge about the available data sources and the nature of the data in each source. The skills and experience needed to point to the correct and valuable data source (e.g. Identify sources, make some source quality assessments) is out of the scope of those business users (see **Table 1**). *"There are tremendous amount of data base connections that have similar names that I don't understand so these differences in the connections and so forth and obviously it's frustrating to build my own advanced thing which takes a lot of times." (business user).* Another barrier prevents users under this mode of engagement from being fully independent (mode 1) is how to prepare data once the data source is identified. As the data is generated from different source, it is expected that it needs some cleaning and manipulation to be prepared for analysis. It requires a specific set of skills such as the ability to correct missing/skewed data, outlier handling, indexing, define measures/dimensions (see 1 for more details) and knowledge of tools and techniques for how to clean and integrate raw data. *"Its tough for me to create a whole new report because I don't really know what data have good quality and clean. I mean what data sources have good and useful data and which one have dummy data" (business user), "...They come to us more to verify that they have built a valid representation of the data. So, they want to know if they used the right fields, if they have added the right filters" (techno-oriented user)*

Mode C (High Dependency): In 'high dependency', business employees are only engaged with the interpretation of the analysis provided from the techno-oriented employees (i.e. Navigate basic system, use information provided to address a task). In this mode, business employees rely fully on the support to solve the analytical task, and they are only involved in the results' interpretation. In other words, techno-oriented users carry out around 70% of the whole process. The techno-oriented gather, prepare, analyse, visualize and communicate the final results to the employees in this mode. *"If people have requests for additional information they want into the data model, we try to provide it based on priorities. This process is rather complicated unless it's something that is already in the staging process and I mean in the data warehouse. So, if it is not, then we take over the report development and we provide the answers directly." (techno-oriented user).* Lacking appropriate technical skills such as data integration, statistical model analysis, etc. , need for more resources and for new data/data sources may encourage business employees to have a high dependency to techno-oriented employees. In this case, the latter is responsible for delivering the final results. *"I have spent some times building a report in Tableau to generate some insights on customer activities but I need to go many years back in time [in the data] so it gets more complicated. I need to get help from the IT/BI department to get some data directly from the data base and provide me an answer to my questions." (business user)*

Discussion and Implications

Our findings suggest that business employees integrate mainly intangible resources with the available resources in an SSBA to generate the desired value. Furthermore, business employees exchange services with techno-oriented employees — the extent of which depends on the different degrees of independence. Due to the complexity of different configurations and participation of more than one actor, our case highlights three main scenarios of engagement. Figure 2 visualizes the three modes of the engagement phase during value co-creation in an SSBA. The X-axis symbolizes the process of value co-creation, and the last intersection point with the three curves represents the generated value. On the other side, the Y-axis shows actors' engagement with data (i.e., business employees are shown at the upper part of the Y-axis and techno-oriented employees at the lower part of the Y-axis). The area under each of the graph's curves provides insights into the amount of work and effort by each of the actors when engaging in a data analysis task. Furthermore, the analytical processes in which business users are involved in each of the three scenarios are nested within each of the areas labelled as A, B, and C.

Drawing from latest research on SSBA (Bani Hani et al. 2017; Imhoff and White 2011), organizations are encouraged to aspire for the 'no dependence mode', that is represented by curve A. In this particular case, business employees are encouraged to solve an analytical task fully independently from techno-oriented employees. To be successful, business users —besides the processes entailed in area B and C—should also be involved in the process of data gathering and data preparation. It implies that they should employ personal institutions and possess the necessary skills (refer to Table 1) to efficiently work with data, BI tools, and tasks. Through an independent scenario, employees' work efficiency will be enhanced primarily because they will feel in control of their work and secondly, because the time it takes to communicate with other actors will be significantly reduced. Moreover, from an organizational perspective, data analytics decentralization (Grossman and Siegel 2014) can be achieved because there will be more autonomous users and fact-based decisions may be infused across levels of an organization (Davenport et al. 2010). Furthermore, by curtailing the time needed for techno-oriented staff to handle daily ad hoc data analytical requests, this scenario is supported by other recent research which indicates that IT/BI resources should be used more efficiently and effectively on strategic projects (Chen et al. 2017; Peppard and Ward 2016). In such mode of engagement, the dominant assumption is that the business user is expected to gather data, prepare data, analyze data, and visualize data. Organizations need to be aware that the first two processes (gather data and prepare data) tend to be rather complex as they may require the use of advanced technical skills such as data manipulation using Structured Query Language (programming language) and many others. However technology is evolving and analytical tools are getting more intuitive and user friendly by lowering the operational complexity of data analysis.

The second preferred mode in organizations is represented by curve B (see Figure 2). It corresponds to a low dependent business employee. Even though business employees possess technical, analytical, and data visualization skills to be involved in the processes of data analyses and data visualization, the lack of other capabilities to engage in other processes, represented in area A, hinder them to successfully complete an already-initiated analytical task. Surprisingly, a lack of self-confidence and trust in data forces business users to contact the techno-oriented users, so that they can obtain advice on technical issues or confirmation on final results. This finding suggests that organizations that strive to reach curve A, should support employees during resource integration and service exchange, mainly to increase their self-confidence and trust in data. First, through training, employees can obtain a more solid knowledge on the data sources, data preparation and data quality. Second, organizations can create 'mentorship' programs where small groups of business users can work for a specific time with techno-oriented users. We believe that this can (hopefully) increase business users' self-confidence on completing an analytical task.

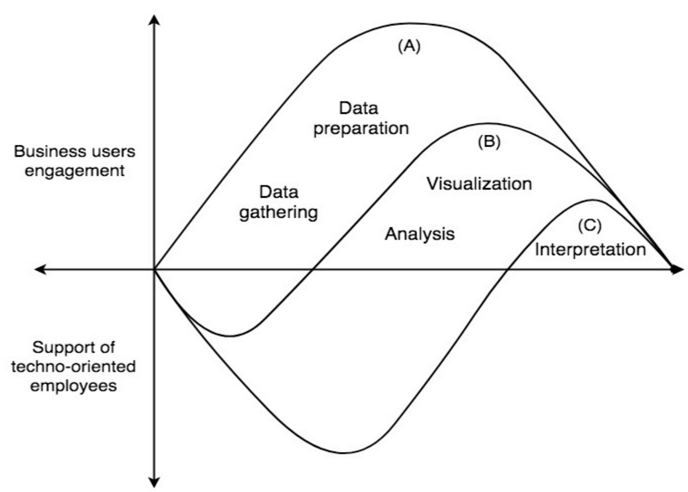

Figure 1: Dynamics in an SSBA

Curve C (shown in figure 2) represents the 'worst' scenario for an organization that has invested in an SSBA approach because of the full involvement of techno-oriented employees. In this case, although business employees can initiate an analytical task by integrating basic business and technical skills necessary for the interpretation process, they lag far behind the necessary resources needed to progress and finish a task. For an organization to progress towards scenario B and ideally A, a data-driven culture should be promoted, thus particular attention should be directed to institutions and institutional arrangements (Vargo and Lusch 2016a). Organizational support is very important because it enables the development of such institutions, and consequently business employees can become more data-driven through enhancing their technical skills and knowledge and adopting attitudes, norms, and rules in line with the organizations' institutions (Vargo and Lusch 2016a). It is worth mentioning that adapting certain work processes to accommodate business employees within this group can also help in shifting to area B and A. By work process we mean practices to pre-define whom gets support in analytical tasks and setting priorities. There should be a sort of balance between providing the required support and pushing for increased independence. To summarize, in order to reap the benefits of an SSBA approach, organizations should shift towards the 'no dependence' mode. Each of the engagement modes entails the analytical process and its corresponding resources that business users should integrate during service exchange. Having said that, the processes and consequently the required resources of the three scenarios are additive, which means that to move from C to A, business users should have the resources of C, B and A. The more involved a business employee is in generating value, the more resources a business employee requires and the less support is needed from a techno-oriented employee.

Our research contributions need to be considered in light of this study's limitations. First, this study does not explore the process on how integration and service exchange occurs, but rather uses these conceptual lenses to analytically study the configuration of business employees and techno-oriented employees when co-creating value in an SSBA. Nevertheless, we believe that this is an opportunity for further research in order to better understand the patterns that may exist during the process of integration and service exchange. Second, future studies could also investigate the mechanisms that facilitate resource integration in each type (A, B and C) and the controlling role of institutions and institutional arrangements. Third, we identify three main scenarios during the engagement phase of business users, however we do not link each of the scenarios with particular values. We believe that this represents an interesting avenue to follow because knowledge of the value generated in each scenario will support organizations to make decisions on an SSBA investment and how to further develop employees.

Conclusion

SSBA, a new approach to BA, aims to empower business employees by making data analytics available to them. Our findings suggest that value co-creation requires specific knowledge and skills from both types of users — business employees and techno-oriented employees — during the different analytical processes. More specifically, the engagement phase is characterised by three modes, which show three ways business employees integrate resources with techno-oriented employees. From an independence perspective, we evaluate the three modes and identify the 'best case scenario'. Departing from that, we discuss the two other modes where business users' independence is threatened by a lack of specific technical resources, trust in data, self-confidence, or institutional support. Finally, we present some practical implications and recommendations for organizations on how to encourage their business employees to become independent during analytical tasks. Finally, this study focuses on the micro-level perspective of value co-creation. It would also be of great interest to investigate value co-creation in an SSBA when external actors such as, customers, governments, and agencies are involved.

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