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Self-Service Business Analytics and the Path to Insights

Integrating Resources for Generating Insights

Bani Hani, Imad

2020

Document Version:
Publisher's PDF, also known as Version of record

[Link to publication](#)

Total number of authors:
1

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Integrating Resources for Generating Insights

IMAD BANI-HANI | DEPARTMENT OF INFORMATICS
SCHOOL OF ECONOMICS AND MANAGEMENT | LUND UNIVERSITY

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Imad Bani-Hani

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DOCTORAL DISSERTATION
by due permission of the School of Economics and
Management, Department
of Informatics, Lund University, Sweden.
To be defended at Holger Crafoords Ekonomicentrum, EC2:101,
17 February 2020.

Faculty opponent
Arisa Shollo, Department of Digitalization,
Copenhagen Business School
Denmark

Organization	Document name
LUND UNIVERSITY	Doctoral Dissertation
	Date of issue 2020-02-18
Author(s): Imad Bani-Hani	Sponsoring organization
	The Swedish Research School of Management and Information Technology

Title and subtitle: Self-Service Business Analytics and the Path to Insights: Integrating Resources for Generating Insights.

Abstract

The nature of today's business demands that Business Analytics (BA) extends to an operational level to better support employees in their decision-making. This is noticeable from the constant requests for new reports and changes in old ones at different employee levels. As a result, BA specialists or other power-users in functional departments are "bombarded" by these requests, and it becomes more of a bottleneck than ever before. This might lead inexperienced users to make critical business decisions without exploring the necessary data. SSBA addresses this need by allowing various employees at different levels across the organization to independently build custom reports and explore previous ones without relying on the IT/BI department. As a result, the end-user role shifts from simply a consumer to a more consumer-producer role. Furthermore, organizations provide different kinds of tools and technologies for their employees to assist them in their daily decision-making. One major challenge in SSBA is that users might engage in a wrong or uneducated self-service step in their data selection or analysis, which will likely lead to wrong business decisions. Therefore, the industry needs to know how those users engage with technology and use the different resources available to generate value in terms of gaining insight from data. Also, from an academic perspective, literature on BA and DSS is abundant and covers many aspects in terms of design, implementation, use in organizations, and BA value's speed of insight and pervasive use. However, SSBA is still under-explored, especially regarding the way resources in an SSBA environment are integrated to generate insight from data especially when employees are expected to be autonomous. Therefore, the aim of this dissertation is to explore and inform organizations about how business users develop insights in an SSBA environment.

This study consists of a collection of five papers, whose findings provide answers to two research questions: RQ1—How do organizations enable an SSBA environment? And RQ2—How do users integrate resources during an analytical task in SSBA? In line with the research questions and the study's aim, Service Dominant Logic was used as a theoretical lens. This dissertation employs an interpretive case study design to investigate SSBA. Three sources of empirical evidence have been used (semi-structured interviews, observations, and documents) to collect data from the top digital marketplace in Norway – Finn.no.

From a theoretical perspective, by portraying Self-Service Business Analytics as an approach to data analytics enabled through the presence of different analytical services such as tools, technologies, and support to assist the user in achieving independence, this dissertation emphasizes the central idea of a service environment and move beyond the classic description of BA and DSS. It also provides a showcase through empirical evidence on how to use S-D logic in IS research and how it could be employed as an analytical lens. Finally, this thesis contributes to both BA and S-D logic literature by theorizing the resource integration patterns, modes of engagement and the self-service environment in business analytics. From a practical perspective, this thesis relates to the industry by highlighting five major points of interest in relation to information authorship, the criticality of the setup phase in SSBA, steps to solve an analytical problem, and the competencies involved.

Key words

Classification system and/or index terms (if any)

Supplementary bibliographical information	Language

ISSN and key title:	ISBN: 978-91-981550-5-1
1651-1816 Lund Studies in Informatics No. 20	

Recipient's notes	Number of pages 165	Price
	Security classification	

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Integrating Resources for Generating Insights

Imad Bani-Hani

LUND UNIVERSITY

About the cover

Tenebrism, from Italian tenebroso ("dark, gloomy, mysterious"), also occasionally called dramatic illumination, is a style of painting using profoundly pronounced chiaroscuro, where there are violent contrasts of light and dark, and where darkness becomes a dominating feature of the image. The technique was developed to add drama to an image through a spotlight effect, and was popular in Baroque painting. Tenebrism is used only to obtain a dramatic impact while chiaroscuro is a broader term, and also uses less extreme contrasts of light to enhance the illusion of three-dimensionality.

The cover basically represents an abstract graphical metaphor of the harmony between individuals walking a path of uncertainty to a common destination or desire. Even though there is an inner belief that this path can be accomplished alone, still a partnership based on support is present. It is rather similar to the main topic of this dissertation where the collaboration between actors in a self-service environment leads to insights into data to ultimately make better decisions. This is the basic goal of Business Analytics.

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Acknowledgments

Abbreviations

SSBA   Self Service Business Analytics

S-D logic   Service Dominant Logic

RI   Resource Integration

BA   Business Analytics

IS   Information System

BI   Business Intelligence

DSS   Decision Support System

SS   Self Service

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1 Introduction

The aim of this chapter is to introduce Self-Service Business Analytics (SSBA), the central topic of this dissertation. In Section 1.1, SSBA will be presented in connection to the Business Analytics (BA) value in organizations including the problem area. In Section 1.2, the research questions and objectives are presented followed by an initial argument on how the research questions will be answered. Section 1.3 describes the delimitation of this dissertation. In Section 1.4, the appended papers are briefly presented and outlined in connection with the research questions. Lastly, a high-level structure of the dissertation is presented in section 1.5.

1.1 Self-Service Business Analytics in Perspective

The value of using Information Technology (IT) in organizations has been a research topic for several decades (Alpar & Kim, 1990; Aral & Weill, 2007; Chan, 2000; Grover & Kohli, 2012; Melville, Kraemer, & Gurbaxani, 2004; Mithas, Lee, Earley, Murugesan, & Djavanshir, 2013; Sambamurthy, Bharadwaj, & Grover, 2003). IT value is generated under certain conditions and manifests itself in several ways such as productivity improvement, business process improvement, and profitability (Kohli & Grover, 2008). The basic argument is not whether IT creates value but rather how it does so, what types of resources are needed (Kohli & Grover, 2008), and how IT is used with other complementary resources (Barua et al., 2010). As such, technology per se is considered as an enabler of value creation and creating value mainly depends on how technology is used in conjunction with other resources such as data technologies, organizational processes, information sharing capabilities, and many others (Devaraj & Kohli, 2001).

Business Analytics (BA), like any other IT resource used in an organization, generates a certain kind of value mainly associated with the processes of data analyses and insight generation for decision making. BA is a type of Decision Support System (DSS) that can be defined as "the techniques, technologies,

systems, practices, methodologies, and applications that analyse critical business data to help an enterprise better understand its business, market itself, and make timely business decisions" (H. Chen, Chiang, & Storey, 2012, p. 1166). Generally speaking, the basic value of BA is to support the decision-making efficiency and effectiveness. One way is by enabling/supporting/enhancing insight generation. The term BA was introduced in the late 2000s as an alternative term to BI pointing to the significance of data analysis in BI (Davenport, 2006). Today, since both BI and BA have similar attributes, they are often used interchangeably.

Undoubtedly, BA has the potential to help organizations better understand their market and create opportunities through the data they can collect and domain-specific analytics they can perform (H. Chen et al., 2012). For instance, research shows that top-performing organizations — in contrast to lower performing organizations— use rigorous data analysis to define future strategies and support daily operations (LaValle, Lesser, Shockley, Hopkins, & Kruschwitz, 2011). This finding was highlighted in a study investigating how smart organizations embed analytics to transform information into insight and then action. Still, the information delivered through BA system is limited to what the IT department provides in terms of analytics and visualizations and cannot satisfy organization-wide needs and business users' requests (Lennerholt, van Laere, & Söderström, 2018).

To address the need for an organization-wide use of data analytics in day-to-day decision-making, organizations have started to enable data analytics throughout the organization by adopting a rather different approach to BA, namely Self-Service Business Analytics (SSBA). SSBA refers to a new approach to BA that aims to decrease the level of employees' dependency on technical people during their engagement with technological resources to generate insights from data (Bani-Hani, Tona, & Carlsson, 2018). SSBA enables users (i.e., non-technical employees) to be more self-reliant. It allows business users to access data and conduct their own analyses for decision-making, with a minimum need of IT department and other power users (Lennerholt et al., 2018). As a result, reports that could take months to deliver can be produced on a timely manner (Imhoff & White, 2011). The most compelling motivation for adopting SSBA is the increased flexibility and independence it offers business users, making them more self-reliant and thus potentially improving the operational efficiency and effectiveness of organizations (Imhoff & White, 2011).

Like BA, SSBA's value is to support the decision-making process, however the self-service approach enhances the traditional BA and enables users to be

involved in data selection, processing and to design reports based on their individual needs. SSBA is becoming a way for organizations to gain and sustain a competitive advantage by becoming more informed and data driven in their decision-making and problem solving (Alpar & Schulz, 2016). That is, the practice of basing decisions mainly on the facts (i.e., analysis of data) rather than intuition and previous experience (Provost & Fawcett, 2013). By making data and analytics accessible to a wider audience in organizations, technical departments become enablers of the self-service approach to analytics rather than responsible for answering user ad-hoc requests and reports. This potentially frees up their time to focus on more strategic tasks such as the data source identification, technology architecture and IT/BI policies. On the other hand, a self-service approach shifts some responsibility from technical departments to business employees (Bani-Hani, Tona, et al., 2018) empowering them by providing more data access and appropriate technical tools to be more self-reliant.

Researchers have explored SSBA from different perspectives ranging from technological design to user acceptance. For example, authors have described SSBA architecture from a technology perspective to promote a deeper understanding of SSBA (Passlick, Lebek, & Breitner, 2017; Spahn, Kleb, Grimm, & Scheidl, 2008; Sulaiman, Gómez, & Kurzhöfer, 2013; Zilli, 2014). Others have explored the factors influencing SSBA acceptance (Daradkeh & Moh'd Al-Dwairi, 2018), user uncertainty during engagement (Weiler, Matt, & Hess, 2019) and the gap SSBA creates between a user and an IT department (Haka & Haliti, 2018). When it comes to the benefit of SSBA, empirical evidence suggests that SSBA enables organizational agility (Bani Hani, Deniz, & Carlsson, 2017) and employee communication and collaboration (Pickering & Gupta, 2015). Yet, there is a lack of knowledge on the way users process data to generate business insights, which is one of the most promoted values of an SSBA environment.

While research on SSBA is growing, this dissertation perceives two lingering concerns seen from two different perspectives contributing to the problem investigated. From a practice perspective, a major challenge in SSBA is that users might engage in a wrong or uneducated self-service step in data selection or analysis (Abelló et al., 2013; Meyers, 2014; Schlesinger & Rahman, 2016; M. Weber, 2013), which likely leads to wrong business decisions. Moreover, there exists a vagueness surrounding the nature of the SSBA environment in terms of how it supports independence in data analytics, what characteristics or factors enable such an environment, and what is the role of the different employees in doing so. Furthermore, organizations are providing different

kinds of tools and technologies for their employees to assist them in their daily decision-making without clear knowledge on how those IT resources are being used or how they contribute to insight generation. Therefore, organizations need to know about the above-mentioned concerns to better manage an SSBA environment and provide the needed support to enable insight generation.

From an academic perspective, literature on BA and DSS is abundant and covers many aspects in terms of design, implementation (Gangadharan & Swami, 2004), use in organizations (Arnott, Lizama, & Song, 2017) and BA value in terms of speed to insight generated and pervasive use (Wixom, Yen, & Relich, 2013). However, there is a lack of knowledge on how the 'self-service' capability of an SSBA brings a significant difference in terms of value, in contrast to the 'traditional' DSS system largely investigated in the IS discipline. Of particular interest is the way that resources in an SSBA environment are integrated, and if this integration is important to the enhancement of insight generation. The results of this study inform not only the industry about SSBA to avoid any possible pitfalls when adopting SSBA, but also further contribute to the BA literature by better describing SSBA and investigating the process through which value, in terms of insight generation, is reached.

1.2 Research Question and Aims

Departing from the previous discussion and the assumption that the technical department cannot satisfy all users requests in terms of data analytics, and also that the SSBA goal is to enable an independent and autonomous business user to generate data insights into a business decision or decision situation while exploring data, the aim of this dissertation to explore and inform organizations how business users develop insights in an SSBA environment.

In such an environment, a business user engages in different processes and interacts with the available resources to generate insights from data. These processes are different from the conventional BA where technical users provide ready analytics to decision makers. Being independent in insight generation does not only depend on competencies and accessibility of resources but also on institutions that enable and control the use and coordination of those resources (Edvardsson, Kleinaltenkamp, Tronvoll, McHugh, & Windahl, 2014). The triadic relationship among the users

(competencies), resources, and institutions in an SSBA environment make the process of generating insights complex and interesting.

Ultimately, fulfilling this aim entails the description of how users enact and interact with resources aligned with their competencies in an SSBA environment to generate insights from data. Also, how such an environment is enabled by the organization and aligned with the users' needs. Hence, it helps the organization to obtain a better understanding of the nature of SSBA environment and how data insights are generated. Departing from the aim of this dissertation and since SSBA is still surrounded by ambiguity, the process of inquiry consists of two main phases. Phase 1 investigates how an SSBA environment is enabled within an organization. To do so, it is crucial to explore SSBA in real settings and related literature to generate a stronger understanding of what SSBA is and what aspect of such an environment enables the self-service approach to data analytics. Since users are more engaged with analytics in SSBA than traditional BA, they do more analytical and technical tasks and invest time and efforts to be more autonomous and independent in task accomplishment. This dissertation expects to identify the main elements that support the notion of independence in the SSBA environment, therefore Phase 1 aims at answering the following research question.

RQ1: How do organizations enable an SSBA environment?

Answering RQ1 provides a better explanation about enabling the SSBA environment, the stakeholders involved in setting up the service (such as data models, tools and other resources important to support the notion of self-service) and its relationship with the use of the service. It further paves the ways for a more informed investigation of SSBA and the resources needed to generate insight from data.

The value of BA is mainly enabling a fact-based decision-making based on data analytics (C. Holsapple, Lee-Post, & Pakath, 2014). BA also saves time and cost by improving information and business process, better decisions and improves strategic performance (Davenport, 2006; Watson & Wixom, 2007). In SSBA, the mentioned values are realized through disseminating analytics (Henschen, 2014; Services, 2012) throughout the organization. SSBA aims to make data analytics accessible to a larger employee base in organizations to perform data access, analysis and reporting independently to ultimately support decision making and actions (Schuff, Corral, Louis, & Schymik, 2016). The employees are in control and have access to a wide range of data

sources and tools to carry-on an analytical task. However, it is unclear how data is converted into insight, how resources are integrated, what controls this process and in which capacity support is needed especially in an SSBA environment. Given that, Phase 2 aims at describing and explaining how resources are integrated to generate insights from data. It is important to explore how a user interacts with the available resources and integrates them with personal competencies and develops the pursued value. The main part of this process is not the tools and technologies used but rather the enactment of those tools and other potential resources. Therefore, Phase 2 addresses the following research question:

RQ2: How do users integrate resources during an analytical task in SSBA?

By answering the second research question, this study theorizes SSBA by describing the types of engagement taking place when generating insight from data and the associated resource integration patterns causing 'data to insight transformation'. This question is rather important as it describes the resource integration and explains the different patterns a user follows to generate insights in an SSBA environment and provides organizations with an opportunity to address any issue affecting the autonomy of its employees during insight generation for decision-making. To do so, it is important to investigate organizations that have adopted a self-service approach to business analytics and examine the employee's engagement with resources and their perception on insight generation.

Through a qualitative case study research design in both previously mentioned phases and using Service-Dominant logic (S-D logic) as an analytical lens, this research allows exploring SSBA in real settings, in a detailed view, to provide a better description of SSBA environment and how resources are being integrated. As a result, this research will empirically shed light on SSBA in organizations and contribute to the literature stream of BA and DSS. It also provides practical implications for practitioners on how to enable an SSBA environment in organizations and more importantly on how to sustain an SSBA user's autonomy by describing resource integration and its patterns.

S-D Logic presents a new view when describing the relationship between a firm and its customers. This new view is built on the idea that services are at the centre of this relationship and the customer is no longer a passive element of the service delivery (Vargo & Lusch, 2004, 2008, 2016a, 2016b). Even though the S-D logic research stream has been focusing on customers as external entities to the organization, S-D logic generalizes it to an actor-to-

actor relationship in any service exchange (Vargo & Lusch, 2016b), therefore S-D logic can also be valuable within organizations.

1.3 Delimitations

The goal of this dissertation is to investigate the way users in an SSBA environment generate insights from data using different resources available. It is not the intention of this dissertation to explore the impact of SSBA on organizational issues either in a positive or negative way, nor the factors affecting the use or usefulness of the SSBA environment resources. The value of SSBA is mainly associated with how the SSBA environment enables the independence of users and how those users profit from the available resources to be independently accessible. The alignment between what an SSBA environment provides and what users need to explore data and generate insights is a key determinant of the SSBA value. There exist different types of value that could be the subject of this dissertation such as the economic value of SSBA however it is the intent to only focus on the insights generated from data as the main value as it is the main trigger for an informed decision making leading to other values.

This dissertation also delimits the interviews carried on to participants experiencing some kind of autonomy in insight generation. As the purpose of this dissertation is to explore the SSBA environment and describe how resource integration occurs, only participants known to be self-reliant and independent to a certain degree in data analysis were interviewed and observed.

1.4 Appended papers

This dissertation adopts a collection of published scientific papers as an approach to accumulating findings from five papers collectively addressing the aim of this dissertation being "***How business users develop insights in an SSBA environment?***"

To do so, the process is divided into two main phases. Phase 1 includes two papers illustrated in Table 1 and Phase 2 also includes two papers illustrated in Table 2. Thereafter, Table 3 contains an unplanned published paper highly

related to the research topic however does not address any research questions. While each paper addresses a specific topic in relation to its related phase, the current chapter integrates the findings from the two phases to provide a higher-level overview and the main contribution of this dissertation.

Table 1:
Description and contribution of the papers in phase 1.

Research question phase 1: *How do organizations enable an SSBA environment?*	
Paper 1	
Title	From an Information Consumer to an Information Author: A New Approach to Business Intelligence
Objective	To explore SSBA and investigate the main factors that are necessary to expand the role of business users from information consumers to information authors.
Method	Systematic literature review of 81 articles
Contribution	This paper provides a new definition of SSBA as an approach to BA. Furthermore, it highlights the duality of high levels of co-production and low levels of dependency as key to the SSBA approach. It also underlines factors and elements that enable and support the notion of a self-service approach to business analytics.
Authors	Imad Bani-Hani (Main author), Olgerta Tona, Sven Carlsson
My contribution	Conducting the database search, the inclusion and exclusion of articles, the analysis and coding of each article organized in an excel sheet containing the relevant information to the literature review including type of methodology, contribution and findings.
Outlet	Journal of Organizational Computing and Electronic Commerce (28:2), pp. 157-171.
Paper 2	
Title	A Holistic View of Value Generation Process in a SSBA Environment: A Service Dominant Logic Perspective
Objective	To explore and explain how an SSBA environment is built while considering the inter-relationship between IT staff, SSBA, and users.
Method	Single case study (13 semi-structured interviews. Secondary data including documents and internal survey)
Contribution	Besides providing a rich description of the phases involved in enabling SSBA, this study also explores the way stakeholders are involved and embedded throughout the process of value generation.
Authors	Imad Bani-Hani (main author), Jorg Pareigis, Olgerta Tona, Sven Carlsson
My contribution	I am the main author of this paper. I have conducted the data collection and analysis. I also wrote the main part of the text with the assistance of the critical input of the co-authors.
Outlet	Journal of Decision Systems, 27:sup1, pp. 46-55

Table 2:
Description and contribution of papers in phase 2.

Research question phase 2: How do users integrate resources during an analytical task?	
Paper 3	
Title	Modes of Engagement in SSBA: a Service Dominant Logic Perspective
Objective	Explore the different modes of engagement the business user experiences while solving an analytical task independently.
Method	Single case study (13 semi-structured interviews. Secondary data including documents and internal survey)
Contribution	Categorizing the user engagement in an SSBA environment into 3 main engagement modes namely; no dependency, low dependency and high dependency including the (missing text). The paper also provides a rich description of each mode of engagement including the major data analytic processes involved.
Authors	Imad Bani-Hani (main author), Olgerta Tona, Sven Carlsson
My contribution	I am the main author of this paper. I have conducted the data collection and analysis. I also wrote the main part of the text with the assistance of the critical input of the co-authors.
Outlet	American Conference on Information Systems (AMCIS) 2019
Paper 4	
Title	Patterns of Resource Integration in the Self-Service Approach to Business Analytics
Objective	Explain and describe resource integration patterns in SSBA and the organizational implications.
Method	22 semi-structured interviews together with documents in the form of organization internal process, problem solving documents and organization survey.
Contribution	Resource integration occurs mainly through two types of interactions between actors and resources within an SSBA environment: direct and indirect interaction. The direct interaction follows a linear enactment of resources whereas indirect has a more clustered nature. The paper also explains the meaning of having clusters during resource integration and possible implications.
Authors	Imad Bani-Hani (main author), Olgerta Tona, Sven Carlsson
My contribution	I am the main author of this paper. I have conducted the data collection and analysis. I also wrote the main part of the text with the assistance of the critical input of the co-authors.
Outlet	53rd Annual Hawaii International Conference on System Sciences, 2020. *(Forthcoming)*

Table 3:
Unplanned publications

Other related papers:	
Paper 5	
Title	Enabling organizational agility through self-service business intelligence: The case of a digital marketplace
Objective	How does self-service business intelligence enable organizational agility in a multi-sided platform?
Method	Single case study (12 semi-structured interviews.)
Contribution	Results indicate that SSBI plays an important role in enabling (1) market capitalizing agility by providing a better understanding of supply and demand participants, more access to traffic data and user clickstreams, fast response to requests, and increased access to supply and demand navigation behaviour,r and (2) better operational adjustment agility by redefining current organizational structures, empowering employees, providing equal access to organizational level data, and opportunities for data manipulation.
Authors	Imad Bani-Hani (main author), Sinan Deniz, Sven Carlsson
My contribution	I am the main author of this paper. I have conducted the data collection and analysis. I also wrote the main part of the text with the assistance of the critical input of the co-authors.
Outlet	Pacific Asian Conference in Information Systems (PACIS) 2017

1.5 Structure of The Dissertation

As stated before, this dissertation is built upon five published papers and an introductory chapter acting as an umbrella section consisting of six chapters structured as follows

Chapter 1 introduces the research topic and background on the problem area from an academic and practical perspective, the aims of this dissertation, and the research question.

Chapter 2 clarifies the concept of business analytics and introduces the self-service approach to business analytics.

Chapter 3 presents the theoretical framework used in the dissertation. The chapter presents a review of extant research related to S-D logic.

Chapter 4 delineates the research approach including research strategy and research design. This chapter describes and reflects on the research approaches and specific methods adopted in each of the appended papers including how each paper contributes to each phase of inquiry specified.

Chapter 5 presents a short summary of the appended papers.

Chapter 6 revisits the research questions by presenting the findings from the appended research papers and explicitly highlights the way the research questions are answered. This chapter ends by presenting unplanned findings that have emerged during this dissertation, and although not related to the research questions, do, however, provide valuable insights into the value of SSBA.

Chapter 7 provides a discussion on theoretical and practical implications this dissertation provides together with discussing limitations and future research.

Chapter 8 concludes this dissertation with an overall final reflection on SSBA.

2 Business Analytics and the Self-Service Approach

This chapter presents a literature review on Self-Service Business Analytics (SSBA) and its related concepts within the scope of this thesis. It starts by presenting a brief history of Decision Support Systems, the Business Analytics sub-domain and how value is generated. Finally, it explores the nature of SSBA and its main promises.

2.1 Decision Support Systems

Decision Support Systems (DSS) are Information System (IS) solutions specifically designed to support complex decision-making and problem solving in organizations (Arnott & Pervan, 2008; Shim et al., 2002). The field of DSS has evolved basically from the conjunction of the theoretical studies on organizational decision-making at the Carnegie Institute of Technology during the late 1950s and technical innovation carried out at MIT in the 1960s (Keen, 1978).

The evolution of IT infrastructure has guided the development and innovation within the DSS field. The first DSS was developed on an IBM 7098 mainframe running a production scheduling application (Ferguson & Jones, 1969) and the first WINDOWS version of a DSS was in the early 90s. The dawn of the Internet has given rise to many new applications of existing technology, especially the rapid dissemination of information to decision-makers using the world-wide-web. Also, the development of Human Computer Interaction (HCI) has affected the use of DSS by providing decision makers a more user friendly and easy to use Graphical User Interface (GUI) that helps in the dissemination of information and faster access (Shim et al., 2002). As a result, decision makers are enabled to access information through electronic services

on their mobile phones or other wireless devices such as portable computers (Earle & Keen, 2002).

DSS is not a homogenous field and has continued to evolve into a main research domain in IS over its 40-year of history. As a result, a number of distinct sub-fields have emerged where several researchers have proposed typologies to describe and classify different types of DSS (C. W. Holsapple, 2008; Power, 2008; Sprague Jr & Carlson, 1982) such as Personal Decision Support Systems (PDSS), Group Support Systems (GSS), Negotiation Support Systems (NSS), Intelligent Decision Support Systems (IDSS), Data Warehousing (DW) and Enterprise Reporting, and Analysis Systems (Arnott & Pervan, 2008). Even though DSS types have a common goal, they differ in their use of technology. For example, GSS and NSS focus on communication and collaboration aspects to facilitate group work contrary to the PDSS, which focuses more on the individual's needs. IDSS highlights the extensive use of artificial intelligence in supporting unstructured decision-making (new and uncommon decision-making). Expanding the accessibility of the tools to decision-makers wherever they may be (Shim et al., 2002) gave the opportunity to PDSS to rise as a dominant research stream in DSS research (Arnott & Pervan, 2014).
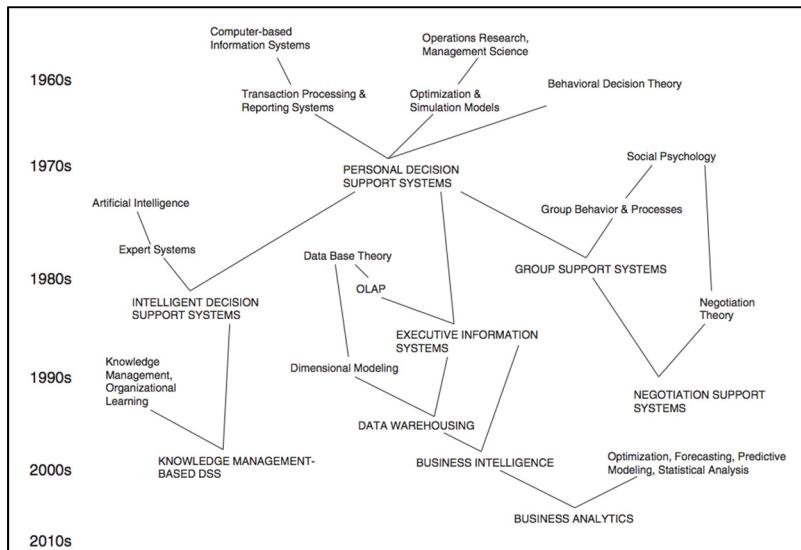
Figure 1:
Genealogy of DSS *(Arnott & Pervan, 2014, p. 271)*

Figure 1 depicts the development of the DSS field and its various types since the 1960s with the Computer-based Information System, PDSS in the 1970s, BI in the 2000s, and BA in the late 2010s, which is the focus of this dissertation. However, what is evident from Figure 1 is that it clearly distinguishes between BI from BA and considers BA as a by-product of BI, along with optimization, forecasting, predictive modelling, and statistical analysis. This view originates from Davenport and Harris (2007) where they describe BA as the extensive use of data, statistical and quantitative analysis, explanatory and predictive models, and fact-based management to drive decisions and actions. However, is it a must for BA to include optimization? Or can we have BA without predictive modelling or any of the factors mentioned above? Many BI studies refer either explicitly or implicitly to optimization, forecasting, predictive modelling and statistical analysis as a part of the BI system (Abbasi, Sarker, & Chiang, 2016; H. Chen et al., 2012; Howson, 2013; Isık, Jones, & Sidorova, 2013; Phillips-Wren, Iyer, Kulkarni, & Ariyachandra, 2015). Even so, some authors consider both terms BI and BA as one and refer to them as BI&A (H. Chen et al., 2012).

Consequently, Arnott and Pervan (2014) acknowledge that there is a very thin line between BI and BA and the BA definition is similar if not identical to the BI definition and most modern large-scale DSS implementations are a complex combination of data processing, reporting and analysis-based applications. Given that, BA and BI are often used interchangeably or together such as BI&A (H. Chen et al., 2012). We can clearly notice that the argument surrounding the nature of BI and BA revolves around the capabilities of these technologies and somehow undermining what it means for the user and its role in defining the nature or BI or BA. Technology advancements have made BI and BA ubiquitous and pervasive to a certain extent. For example, when booking a hotel online, the customer is presented with the most convenient and value deals based on data analytics. When looking to purchase an electronic device, many websites provide online comparisons of the same product from different vendors, also based on data analytics. Even our smartwatch and phone might alert us on the need to do some exercises when it is time, again, based on data analytics. Therefore, we argue that rather than defining BA, BI, and other DSS types solely in terms of technology and data the focus should be on the user perception and/or interaction.

2.2 Business Analytics

As stated previously, in the early 1960s, decision-support systems were the first applications developed to assist decision-making. During the last few decades, various decision-support applications have emerged to meet organization demands (such as an executive information system (EIS), online analytical processing (OLAP), and predictive analytics), which in turn have expanded the decision-support domain (Watson & Wixom, 2007). Business Intelligence (BI), as a type of DSS, has been introduced in the early 90s by an analyst at Gartner Group to describe the analytical applications and processes that support decision-making in organizations. Business Intelligence (BI), and frequently referred to as Business Analytics (BA) is "a broad category of applications, technologies and processes for gathering, storing, accessing and analysing data to make better decisions" (Watson, 2009, p.491). The BA architecture consists of several parts collectively contributing in processing data that finally produce insights for decision-making (See Figure 2).
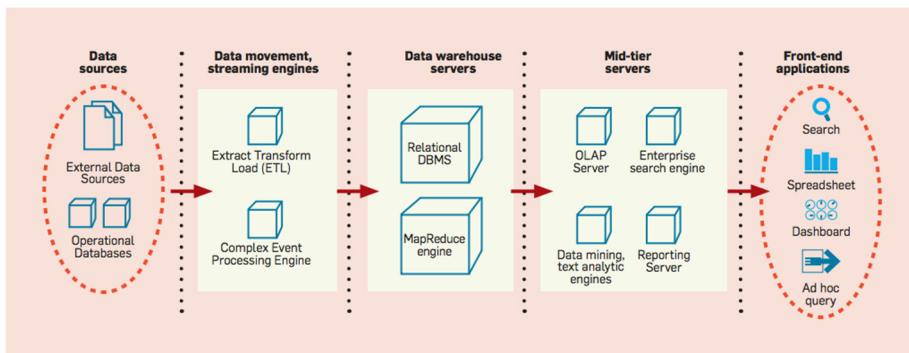
Figure 2:
Business analytics architecture *(Chaudhuri, Dayal, & Narasayya, 2011)*

During the data gathering process, BA connects to a variety of internal and external sources (Gibson & Arnott, 2005), e.g., external customer reports, surveys, enterprise resource planning (ERP), customer relationship management (CRM), supply chain management (SCM) and other legacy systems. In addition, data is Extracted, Transformed, and Loaded (ETL) (Gibson & Arnott, 2005) into data warehouses, data marts (March & Hevner, 2007; Watson, 2009) or recently to Hadoop clusters (Phillips-Wren et al., 2015).

The ETL process is considered a critical part in the BI architecture. It constitutes the main interface between raw data (not processed data) and meaningful, integrated, consolidated and clean data. In other words, extracting data involves gathering data from appropriate sources, with data usually available in flat file formats such as comma-separated values (CSV), Excel (XLS), or .txt or operational databases (Bansal & Kagemann, 2015; Chaudhuri et al., 2011; H. Chen et al., 2012). The transformation phase involves cleansing data, sometimes invoking quality checks to comply with the target schema (Bansal & Kagemann, 2015; Chaudhuri et al., 2011; H. Chen et al., 2012). Typical transformation activities involve removing duplicates, checking for integrity constraint violations, filtering data based on defined regular expressions, sorting and grouping data, and applying built-in functions where deemed necessary. Finally, propagating the data into a target relational database, data mart, or data warehouse for client use (Bansal & Kagemann, 2015; Chaudhuri et al., 2011; H. Chen et al., 2012). After data is stored, it is available to be analysed through a variety of analytical tools and converted into information. Users, via different devices such as a PC, laptop or mobile device, can access information necessary for decision-making and action-taking.

The mid-tier server shown in Figure 2, represents the layer where cleaned and integrated data is being processed. This layer provides specialized functionality for different BI scenarios. For example, Online Analytic Processing (OLAP) servers efficiently present a multidimensional view of data to applications or users and enable, what is considered common BI operations, such as data filtering, aggregation, drill-down, and pivoting (Jukic, Jukic, & Malliaris, 2008). Furthermore, "in-memory BI" engines use today's large main memory sizes to dramatically improve the performance of multidimensional queries by hosting the data in-memory and prevent often communicating with the database (Howson, 2013; Wixom et al., 2013). Moreover, reporting servers integrate definition, efficient execution and rendering of reports to facilitate report generation (Chaudhuri et al., 2011) —for example, reporting the total sales by region for the current year and comparing it with sales from the previous year.

Data mining engines enable an in-depth analysis of data that surpass the potential of OLAP or reporting servers, and provides the capability to build predictive models based on statistical analysis (Vercellis, 2009; H. Wang & Wang, 2008) and answer questions such as: 'which existing customers are likely to respond to my upcoming new service campaign?'. Text analytics such as text mining can analyse huge amounts of text data (such as survey responses

or comments from customers) and extract valuable information that would otherwise demand significant manual effort (Tan, 1999). A good example of text mining is searching for what services are mentioned in the survey responses and the topics that are frequently discussed in connection with those services (positive or negative comments). There are several known applications through which different users perform BA tasks such as spreadsheets, performance management applications that enable decision makers to track key performance indicators of the business using visual dashboards, tools that allow users to perform ad hoc queries (Chaudhuri et al., 2011) and make informed business decisions.

Users vary in their analytical skills and capabilities. Aside from the position they hold in an organization, the difference is partly explained by the employees' education, background, experience, training and motivation to learn analytical skills. Users can be categorized in three types —in a form of a pyramid— based on the number of each user category in an organization (Dinsmore, 2016; Phillips-Wren & Hoskisson, 2015; Phillips-Wren et al., 2015).
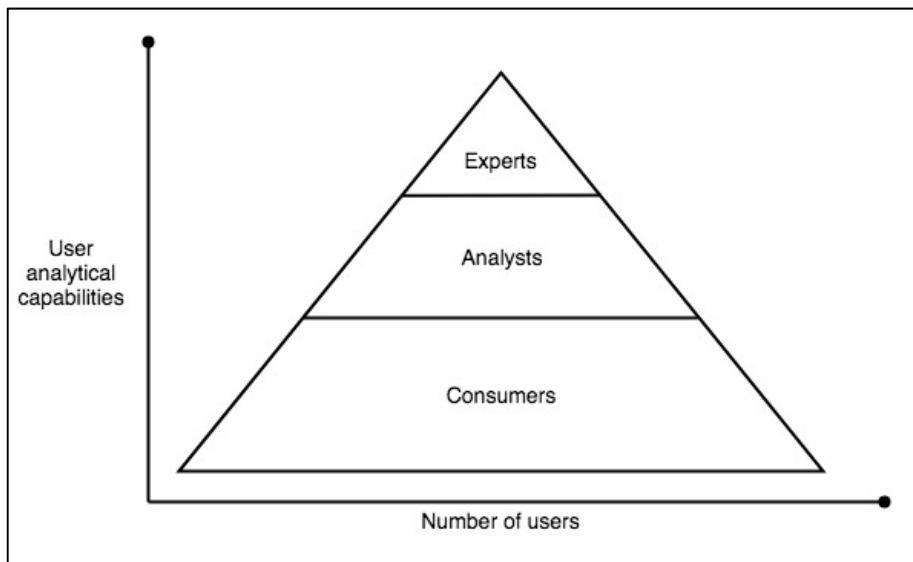
Figure 3:
The user pyramid headcount in organizations *(Dinsmore, 2016)*

The most common users in organizations are the information consumers, such as sales, marketing, and operations employees who basically are responsible for the daily transactions and activities in an organization. They tend to have access to minimal tools and technology related skills and prefer information that does not require effort and technical skills (Dinsmore, 2016).

A second type of user encompasses analysts, who have a set of skills enabling them to explore available data through analytical tools and use analytics in their work. The third type includes experts who possess advanced skills regarding data manipulation and analytics software. Experts typically spend 100% of their time in developing advanced analytics, maintaining data quality and evaluating analytical models (Dinsmore, 2016; Phillips-Wren & Hoskisson, 2015; Phillips-Wren et al., 2015). Table 4 describes the three types of BA users and their characteristics.

Table 4:
BI&A user type based on *(Eckerson, 2011), (Phillips-Wren & Hoskisson, 2015)*

User type	Description	Characteristics
Consumers: Business leaders Information users	Casual users, external users such as customers and suppliers who may connect via applications that depend on analytical processing without being aware of the complex processing involved.	Basic analytical capabilities and domain-based expertise.
Analysts: Strategic analyst Functional analysts	Users who have more analytical skills than business users who interactively perform deeper analysis to support their decision-making	Analyses data, understand how data is organized, retrieve data via ad hoc queries, produce specialized reports and build what-if scenarios.
Experts: Data scientists Developers Analytics specialists Statisticians	Has a strong background in mathematics, statistics, and/or computer science, equally strong business acumen, and an ability to communicate with both business and IT leaders in a way that can influence how an organization approaches its business challenges with the help of data	Develop descriptive and predictive models (perhaps using the discovery platform; e.g., Sandbox), evaluate models, and deploy and test them through controlled experiments.

In a typical scenario, business users, being information consumers, consume information from BA that is made available to them by business analysts, through a request, or based on a regular agreement between departments. Thus, business users actually engage with BA only once data is converted into information. Hence, through BA they consume information, which they then convert into knowledge based on their intuition, previous experience, task and context. Afterward, they apply the knowledge produced to take decisions and actions. Interestingly, in this phase, BA supports a business user only during information use. (Phillips-Wren et al., 2015)

This scenario is very common in organizations where the technical department controls most of the process of data analytics and only provides certain interfaces with limited functionalities to the users especially the consumers. The problem arises once this type of user requests new interfaces or analytics with new data or specific data to their business. Since consumers constitute the largest number in an organization, the many requests create an overload on the technical department who cannot address all needs.

2.2.1 The Value of Business Analytics

The value of a BA system is mainly associated with decision making through insight discovery (Shanks & Sharma, 2011; Someh & Shanks, 2013; Wixom et al., 2013). To support decision making and insight discovery, BA takes data into a journey of cleaning, integration, validation, organization, and processing until a more comprehensible and value embedded visualization is presented to decision-makers, who in turn develop insights to make informed decisions and take competitive actions. According to Seddon, Constantinidis, Tamm, and Dod (2017, p. 242), insights are "the gaining of a deep or deeper understanding of something, arising from use of business analytic (BA) capabilities. Some insights are more valuable, or more profound, than others. In the simplest of cases, insight may arise simply as a result of reading a new report or viewing a dashboard." Organizations might possess analytical capabilities and resources however value emerges only when the generated insights originating from the BA result in decisions and actions become realized (Davenport & Harris, 2007).

BA value can be perceived from two different perspectives. First, from an organizational perspective, the BA insights per se are not the value itself but rather what leads to a value-generating action to improve performance or develop a service. Second, from a user perspective, the BA insights are perceived as value since they directly assist users in making an informed decision that leads to a certain action. This is very similar to how Vargo and Lusch (2016a, p. 47) describe value stating that "Value is always uniquely and phenomenologically determined by the beneficiary".

In organizations, the value of using BA manifests itself as two main types: tangible and intangible (Shanks & Sharma, 2011; Someh & Shanks, 2013; Wixom et al., 2013). Tangible values are the values that can be perceived and measured such as productivity improvement, cost saving, and time saving. In contrast, intangible values are the values that are not directly perceived and

cannot be measured such as innovation, reduction in uncertainty and data driven culture. Both types of values mostly occur if different organizational resources are combined together and used in conjunction (Aral & Weill, 2007; Devaraj & Kohli, 2003). Such resources are comprised of human capabilities and competences, technological infrastructure including BA systems and other organizational resources. This explains why BA models somehow vary as they might focus on a different type resource (Accenture, 2013; Liberatore & Luo, 2010; Sabherwal & Becerra-Fernandez, 2013; Shanks & Bekmamedova, 2012).

However, Seddon et al. (2017) developed a model describing how business analytics contribute to organizational performance. The general model consists of a process model and a variance model. The variance model mainly aims at better describing what a manager can do to better realize greater value from BA. In contrast, the process model aims at describing how individual organizations use BA to generate business value based on the argument that "the prime drivers of business value from BA are actions driven by new insights and improved decision making" (Seddon et al., 2017, p. 244). Since this dissertation is mainly concerned with how business users develop insight in an SSBA environment, the focus will mainly be on the process model.

The process model consists of two main parts and three paths: the first part (left-hand side) and the second part (right-hand side) (see Figure 4).
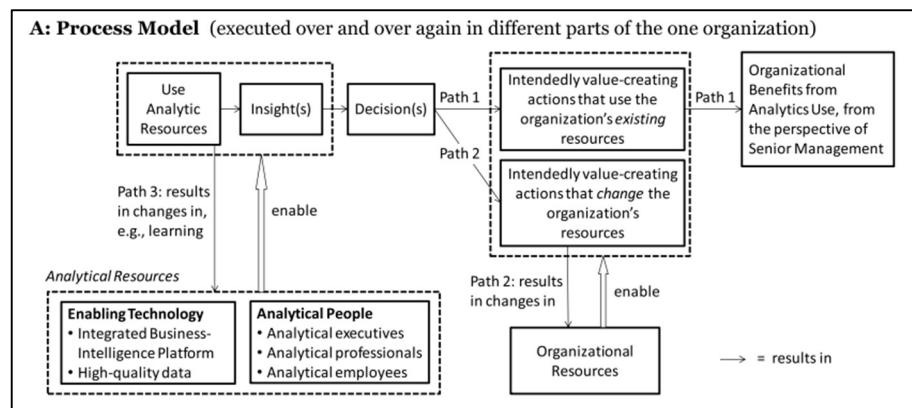
Figure 4:
Process model of BA value *(Seddon et al., 2017)*

The first part describes the use of business analytics resources to produce information, insights, and decisions supported by analytical resources. The second part is concerned with the use of the entire organization's set of resources to produce business value based on the outcome of the first part. Path 1 basically represents the use of the organizational analytical resources by individuals to generate insights leading to decision leading to value creating actions, and, in turn, leading to organizational benefits. For example, the analysis of customer data to make marketing campaign decisions and actions targeting specific group with advertisements. Path 2 highlights the use of analytical resources by individuals that might lead to insights and decisions that have a direct impact on organizational resources. As an example, the use of customer data to identify problems with a certain service provided. Path 3 points to the idea that the use of analytical resources sometimes leads to a direct change in those same resources, as in the need to include a dataset or improve data quality. This dissertation aim is to investigate how business users develop insights in an SSBA environment therefore the focus will be mainly on the top and bottom left dotted boxes in Figure 4.

Seddon et al. (2017) makes two important points regarding how value is generated in organizations. First, they implicitly refer to the importance of using and combining analytical resources in generating insights for decision making, which is clear in the top left box in Figure 4. This view is consistent with several studies investigating value generation from BA (Blyler & Coff, 2003; Shanks & Sharma, 2011; Sharma, Reynolds, Scheepers, Seddon, & Shanks, 2010; Someh & Shanks, 2013). Second, they state that "value from BA may be generated by many people in an organization, not just data scientists" referring to Davenport and Patil (2012). They further argue that many people have access to BA systems in an organization, and all of them have the potential to develop useful insights leading to a collective value generation which is a fundamental driver of BA benefit. This view is also consistent with other studies investigating BA pervasive use and dynamic capabilities of BA (Kohavi, Rothleder, & Simoudis, 2002; Wixom et al., 2013). Both points closely relate to the idea that the overall value of BA is co-created by multiple actors integrating and combining resources in an ecosystem supporting access to BA resources.

Even though this model is comprehensive, it still takes a broad perspective and does not clearly explain how analytical resources are used within an environment that supports insight generation in decision making. In other words, the first three boxes (i.e., use analytic resources, insight(s) and

decisions) can greatly benefit from more explanation as they are the main triggers for the value generation and can lead to interesting practical and theoretical implications.

2.3 The Self-Service Approach to Business Analytics

The nature of today's business requires that BA extends and reaches operational level employees to support them in their tasks. This is noticeable from the constant requests of new reports and changes in old ones at different employees levels within the organization (Yu, Lapouchnian, & Deng, 2013). As a consequence, BA specialists or other more technical oriented users at functional departments are "bombarded" by these requests are becoming more of a bottleneck than ever before (Kobielus, Karel, Evelson, & Coit, 2009) where business users facing critical business decisions may act without fully exploring data (Abelló et al., 2013)

Before discussing SSBA, it is important to mention that the general concept of self-service in data analysis is not new. Scholars have been exploring it for decades. However, technology changes are aiming to create more sophisticated, easy to use, and more convenient information systems to support our needs. A close example of such concepts are the End-User-Computing (ECU) and User Developed DSS (UDDSS) (Carlsson, 1993). Tracing EUC back in time, the early 80s denote an interest in this area of IS (Corea & Lupattelli, 1972). ECU is the adoption and use of information technology by personnel outside the information systems department to develop software applications in support of organizational tasks (Bedford, Maddess, Rose, & James, 1997; Bullen, 1986; Fenton & Doyle, 1969; Lehman, 1985; Leitheiser & Wetherbe, 1986; Panko, 1987; Sipior & Sanders, 1989)

EUC emphasizes the computing literacy and skill of employees required to be able to use software applications by either advanced users, such as developers, or regular users like data entry personnel. This should apply similarly to systems that vary in their complexity from relatively simple application to a comprehensive and complex information system (Suzuki, 2002). Many studies have been published in the area of EUC, focusing on several phenomenon related to the IS discipline. Several examples are the adoption of spreadsheet software, the application of role theory to the end-user development (R. Ryna

Nelson, 1991), the impact of user-developed decision support systems on the individual learning (Carlsson, 1993), the training of the end-users (R. Ryan Nelson & Cheney, 1987), the measuring of end-user computing satisfaction (Doll & Torkzadeh, 1988, 1991), user information satisfaction (Iivari & Ervasti, 1994), and measures for software acceptance and use (Deuticke, 1972).

As technology evolves and the need for informed decisions based on data analysis increases, software applications are being designed to minimize the cognitive requirement (such as advanced knowledge and skills to operate certain technological tools) needed to accomplish a task, especially when it comes to processing a huge amount of data and draw insights. SSBA has emerged as a new approach to BA allowing various employees at different organizational levels to independently build custom reports and explore previous ones without relying on the IT/BA department (Abbasi et al., 2016). As a result, the user role will shift from a consumer to more of a consumer-producer and expand the involvement of business users allowing them not only to consume information but also to author information (Bani Hani, Tona, & Carlsson, 2017; Imhoff & White, 2011). The user is no longer just exploiting the data but also exploring it (Stodder, 2015) by independently accessing data and producing information in the form of reports and simple analytical queries without relying on business analysts or data scientists who typically are part of an IT/BA department (Abbasi et al., 2016).

Furthermore, Imhoff and White (2011) have presented a model that defines the core objective of SSBA, namely; "Make BA Results Easy to Consume and Enhance", "Make BA Tools Easy to Use", "Make Data Warehouse Solutions Fast to Deploy and Easy to Manage", "Make Data Sources Easy to Access" (Imhoff & White, 2011). These four main objectives of SSBA are centred on making users more self-reliant and empowered through an SSBA environment (Imhoff & White, 2011).

Imhoff & White explore some interesting aspects and pitfalls of SSBA. Particularly, one of the main challenges of SSBA, also highlighted by Alpar and Schulz (2016), which is about adjusting the level of flexibility through self-service to match the level of analytical and technical skill of the SSBA users. Since these levels may vary widely depending on the organization it can be a challenging task, but it is as rewarding as it is paramount to reap the full benefits of SSBA. Imhoff and White (2011) discuss this aspect through all of the four objectives and points out that one way to solve this problem is by

implementing SSBA tools that are more intuitive to use (Imhoff & White, 2011).

From an organizational perspective, SSBA enables an equal control and access to data and BA tools, which has the potential to increase the number of original insights generated within the company (Imhoff & White, 2011). This, in turn, helps the organization gain a more general vision and to develop strategies with a higher degree of intelligence. Furthermore, SSBA promotes organizational efficiency in regard to time. Since SSBA enables information workers to create their own tailored analytics in accordance with their needs and wants, rather than relying on BI/IT department (Imhoff & White, 2011). The notion of that improved efficiency on an individual level might impact organizational efficiency and is also true in the aspects of collaboration and sharing of BA resources and expertise. For example, SSBA offers the opportunity for an individual user to mark the incorrect data or highlight relevant relationships in data sources, and then share this information with other employees (Abelló et al., 2013; Imhoff & White, 2011).

Also SSBA can enhance organizational agility by strengthening "market capitalizing agility" described by Lu and Ramamurthy (2011) as to how well an organization can adjust and improve its products and services to match changing customer demands. Also, "operational adjustment agility" refers to how fast and accurately an organization can adapt to changes in external factors, by adjusting their internal processes. This type of agility enables the organization to effectively exploit external variations by aligning internal and external changes in an advantageous manner (Lu & Ramamurthy, 2011). Both types of organizational agility benefit from an SSBA environment, since it provides the organization with the necessary capabilities to understand its customers and quickly respond to shifts in the market.

There are many attempts from both industry and academic researchers to define SSBA, as shown below in Table 5 however confusion is still dominating and the way SSBA is perceived is still vague.

Table 5:
Current SSBA definition

Reference	Definition
Imhoff and White (2011)	The facilities within the BI&A environment that enables BI&A users to become more self-reliant and less dependent on the IT organization
Gartner IT Glossary (2016)	Is a form of business intelligence (BI) in which line-of-business professionals are enabled and encouraged to perform queries and generate reports on their own, with nominal IT support. Self-service analytics is often characterized by simple-to-use BI&A tools with basic analytic capabilities and an underlying data model that has been simplified or scaled down for ease of understanding and straightforward data access.
M. Weber (2013)	Is a BI&A system that enables business executives, managers, operational decision makers, analysts, and knowledge workers to access the information they need whenever and wherever they need it, providing key data to support the decisions and actions that are critical to business success.
Pal (2016)	Self-service analytics can be defined as a simple form of business intelligence (BI), where business users are empowered to access relevant data, perform queries and generate reports themselves with the help of easy-to-use self-service BI&A tools. The entire self-service process is simplified or scaled down for better usability. The purpose of self-service analytics is to enable business users to perform their day-to-day analytics tasks themselves ...
Schuff et al. (2016)	Is the BI&A ability to give business users access to selection, analysis, and reporting tools without requiring intervention from IT

Imhoff and White (2011) refer to SSBA as a facility within the BI&A environment. Gartner IT Glossary (2016) and M. Weber (2013) describe it as a BI&A system, and Schuff et al. (2016) labels SSBA as an ability. There is no clear definition of SSBA. So, what exactly is SSBA? Is it a capability within the BI&A environment, does it represent a new system or is it a new approach to BI/BA? Is SSBA viewed from a technological lens or does the user play a more important role in defining SSBA?

To have a more precise understanding of what the definition of SSBA is, it is important to first see what constitutes it. It is obviously clear that it is comprised from two terms; Self-Service (SS) and Business Analytics (BA). The first part, SS, is more related to the individual behaviour and preference to be independent, in control, save time, cost and to be efficient (Bani Hani, Tona, et al., 2017; Bateson, 1985). It denotes an attitude or ideology toward approaching a certain activity or task. In technology, many studies have investigated the preference of a customer in using a self-service channel over a service encounter (Curran & Meuter, 2005; Dabholkar, 1996; Dabholkar & Bagozzi, 2002; Dibb, Marylyn Carrigan, Schuster, Drennan, & N. Lings, 2013; López-Bonilla & López-Bonilla, 2013; Meuter, Ostrom, Roundtree, & Bitner, 2000; Scherer, Wünderlich, & von Wangenheim, 2015). It is also present in data analytics for decision making where users tend to be more engaged in self-service activities to solve an analytical task without relying on IT experts

(Alpar & Schulz, 2016; Bani Hani, Deniz, et al., 2017; Bani Hani, Tona, et al., 2017; Barc, 2014; Imhoff & White, 2011; Schuff et al., 2016). The self-service phenomenon is not only present in technology, but in our daily lives. For example, some people prefer to service their own cars such as changing the engine oil (if they have the expertise) instead of going to the service centre and some others prefer to self-study and home study instead of going to an educational institution. This phenomenon is gaining much attention because of its increase in our societies especially when many services are shifting from a service encounter (human to human interaction) to digitalized self-services (human to technology interaction) such as in banking, airlines, supermarkets, hotels, etc (Curran & Meuter, 2005; Dabholkar, 1996; Dabholkar & Bagozzi, 2002; Meuter et al., 2000). The second part is BA, previously discussed in section 0, and is a collection of technologies and processes that are available for data analysis and decision-making rather than a single information system.

SSBA can be seen first as an approach to business analytics rather than the adoption of a certain technology. In other words, it is the technology readiness within the organizational environment and the willingness of a user to engage in self-service activities using the resources available for the ultimate aim of solving an analytical task independently. Second, the SSBA approach is enabled by an environment that provides services to support independence of users. Those services, such as tools and technology, access to clean and meaningful data, technical and business support when needed, are provided and managed by an IT/BI department. In other words, the IT/BI department provides specific services to enable SSBA and in turn, the users engage in data analytics independently using those resources. Once the IT/BI department enables such a service environment, they can focus on more advanced tasks rather than answering individual ad hoc requests. As such, this thesis depicts SSBA environment as a service environment within the organization aiming at facilitating the self-service approach to BA.

2.4 Concluding Remarks

The value of a BA system is mainly associated with decision making through insight discovery. Several scholars confirmed that the value of BA increases through two main dimensions: first the combination of resources to generate insights, and second, the more users have access to BA to generate insights the higher the value will be. It implies that giving access to analytics throughout the organizations and providing an environment with resources supporting data analytics has a positive impact on the value generated from BA. Self-service Business Analytics is an approach to data analytics aiming at creating a more independent user in fulfilling information needs for more informed decision-making. It is important to understand that SSBA is not a capability, a tool, technology or even an extension of a BA system. It is rather a service environment containing different resources to enable the self-service approach to business analytics. In such an environment, users can serve themselves and change their status from information consumers to information authors and gain more freedom and independence in data analytics. The next chapter will have more focus on describing the service environment from an S-D logic perspective and what makes such environment important in SSBA.

3 Service Dominant Logic

This chapter presents the main conceptual lens adopted in this dissertation. First, this chapter presents Service Dominant Logic (S-D logic) and its five axiomatic assumptions. Then the core elements of S-D logic are discussed with a special focus on Resource Integration (RI). Finally, a discussion about the importance of S-D logic especially in the IS field is presented.

3.1 What is S-D logic?

Historically, services were seen on the opposite side of goods. For example, goods-related industries and manufacturing industries, such as agriculture, mining, and cars, have been viewed as extractive. On the other side, service industries, such as health care and entertainment were industries that had a focus on non-tangible offerings and not physical goods.

In 2004, Vargo and Lusch (2004) introduced a new way of looking at service delivery by proposing a new dominant logic denoted as Service Dominant logic (S-D logic). S-D logic is a theoretical framework (sometimes used as a lens) for explaining and describing value creation among configurations of actors through the exchange of resources (Vargo & Lusch, 2018). The fundamental notion of S-D logic is that humans apply their competences (resources) to benefit others and equally benefit from others' applied competences within service-for-service exchange (Vargo & Lusch, 2004). They further define service as a process where one uses personal resources and competences for the benefits of another entity or the entity itself (Vargo & Lusch, 2004). In their view, services are not a different form of goods, instead, they constitute the process whereby the exchange takes place and goods facilitate this process. For example, computers are goods that facilitate the process of processing information through the use of user competence.

S-D logic claims that in order to create value, actors engage in interdependent and reciprocally beneficial service exchange (Lusch & Vargo, 2014). Value creation emerges in an interconnected network of resource exchange among actors, and thereby it is conceptualized as value co-creation (Vargo & Lusch, 2008; Vargo, Maglio, & Akaka, 2008). Recently, S-D logic has shifted towards a more dynamic and system-oriented view in which value co-creation is managed through shared institutions (norms, symbols, competence) on a broader scale of resource integration and service exchange process (Vargo & Lusch, 2017).

Figure 5:
Value co-creation cycle *(Vargo & Lusch, 2016a)*

Figure 5 depicts the S-D logic process of value co-creation through five main components, namely: actors, resource integration, service exchange,

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institutions and institutional arrangements, and service ecosystem. Collectively, they denote value co-creation in S-D logic and serve as the basis for describing S-D logic axioms.

S-D logic highlights five core Foundational Premises (FP), which have recently (Vargo & Lusch, 2016a) been identified as axioms (see Table 6). S-D logic represents a "dynamic, continuing narrative of value cocreation through resource integration and service exchange" (Vargo and Lusch (2016b, p. 47) developed by the increasing number of academic disciplines through building on S-D logic FP's with a special focus on the five axioms.

Table 6:
Axioms of S-D logic *(Vargo & Lusch, 2016a)*

	Axiom
Axiom 1/FP1	Service is the fundamental basis of exchange
Axiom 2/FP6	Value is co-created by multiple actors, always including the beneficiary
Axiom 3/FP9	All social and economic actors are resource integrators
Axiom 4/FP10	Value is always uniquely and phenomenologically determined by the beneficiary
Axiom 5/FP11	Value co-creation is coordinated through actor-generated institutions and institutional arrangements

Axiom 1 puts service at the heart of the exchange. S-D logic defines service as "the application of specialized competences (i.e., operant resources: knowledge, skills) through deeds, processes, and performances for the benefit of another entity, or the entity itself" (Vargo & Lusch, 2008, p. 26). In service systems, actors linked with "shared institutional arrangements" such as competencies, rules and norms (Akaka & Vargo, 2015, p. 456) integrate specific resources (operant and operand) to co-create value (Lusch & Vargo, 2006). In other words, service is exchanged between actors where goods are used as service enablers having in mind that all business are service businesses and all economies are also service economies (Lusch & Vargo, 2014).

Axiom 2 challenges the traditional view in which firms are seen to create value. It rather suggests that value is always co-created by multiple actors directly or indirectly through goods. This implies that value does not arise before any transaction but only after the exchange of resources, in a specific context, and happens among the actors. Value creation does not stop there; it continues its expansion through social and economic exchanges where the new values may be used for new resource exchange (Vargo & Lusch, 2017). Initially, the aim of this axiom was to highlight the shift of focus in terms of value creation from the firm side to the customer side and from value-in-exchange to value-in-use.

Also value-in-context has been used in S-D logic to emphasize that value must be related to the context that the beneficiaries are acting in conjunction with available recourses and other involved actors (Vargo, 2009). Recourse integration by multiple actors in S-D logic underpins the collaborative nature of value creation, and at a higher level of aggregation (at a societal level) value co-creation becomes a service-for-service exchange (Chandler & Vargo, 2011).

Axiom 3 points to the fact that all actors in the value creation process not only provide service but also integrate resources from many other resources (Vargo & Lusch, 2011; Wieland, Koskela-Huotari, & Vargo, 2016). It implies that that the resource integration is not only limited to the firm providing the service but also to a wide range of actors' resources such as private (self, friends, and family), market (from other actors, economic exchange) or from public sources (communal and governmental sources) and highlights the broad view networked nature of value co-creation. "This resource integration not only occurs with the resources directly available to actors involved in an exchange but also indirectly with the resources and actors that provide these resources in a network of other resource-integrating actors." (Lusch & Vargo, 2014, p. 56).

Axiom 4 emphasizes that all offerings, whether market offerings, service provisioning, or goods, are uniquely perceived and integrated by the actors. Consequently, value is also experienced differently (Lusch & Nambisan, 2015). It follows that value must be understood from a broader perspective, as it is a result of a combination of different resources, thus it is dominantly unique to the single actor and can only be determined by the actor itself (Chandler & Vargo, 2011).

Finally, Axiom 5 draws attention to the importance of institutions and the processes in such institutions for value co-creation. An institution does not mean the organization but rather the norms, rules and beliefs that humans have developed over years which control actions (North, 1990; Richard, 2001). Vargo and Lusch (2016) have described the role of institutions and institutional arrangements in enabling actors to accomplish an increasing level of resource integration for value co-creation constraint by time and cognitive abilities. It is noteworthy that institutions are not static and fixed. Actors can break old institutions, make new institutions and maintain valuable ones (Koskela-Huotari, Edvardsson, Jonas, Sörhammar, & Witell, 2016). It implies that there exist different types of institutions such as personal belonging to the actors and organizational belonging to the service ecosystem. Also, Scott (2013) has developed a widely accepted categorization built on three main pillars: regulative, normative and cognitive.

First, the regulative pillar mainly consists of formal rules that enable or constraint the actors' behaviour in an effort to avoid any kind of formal sanctions. Second, the normative pillar consists of norms and rules that are defined based on an actor perception of social benefit or constraints. Third, the cognitive pillar consists of a set of beliefs originating from actors perception and personal interpretation of their environment, hence represents the actor's connection with the field (Scott, 2013). Obviously, the rules, norms, and beliefs originating from the three pillars influence an actor's efforts in accessing, mobilizing, combining, sharing, transforming, and applying resources during resource integration and ultimately in the coordination of resource integration itself (Edvardsson et al., 2014).

The five axioms are fundamental to understand S-D logic and its philosophy. All resource integration and service exchanges happen within an ecosystem referred to as service ecosystem. A service ecosystem is "a relatively self-contained, self-adjusting system of resource-integrating actors that are connected by shared institutional logics and mutual value creation through service exchange." (Lusch & Vargo, 2014, p. 66).

The service ecosystem in S-D logic is considered as the medium or the context in which value co-creations occurs. All actors exist in an ecosystem either on a small scale such as the internal organization environment or on a larger scale such as the society. However, the key point is that all resource integrating activities occurs in a service ecosystem that support such activities. If we take SSBA for example, the service ecosystem is the internal organizational environment in which the users integrate resources to generate insights. This environment is optimized and managed by the IT department through the provision of analytical tools, clean and integrated data sources, support, and training. Such an environment enables the business user to be more independent and self-reliant in data analytics, hence generating the foreseen value.

3.2 Resource Integration in S-D logic

Resource Integration (RI) is a concept in S-D logic that is built upon the basic premise that resources are provided by all actors (Vargo & Lusch, 2018). RI has been defined as "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,

Winklhofer, & Temerak, 2012, p. 2). The notion of the customer-producer (co-producer) dyad has been generalized to actor-to-actor networks (Vargo & Lusch, 2016b).

The actors integrate resources through service exchanges (Vargo & Lusch, 2018). The notion of RI in S-D logic comprehensively takes into account the vast and intrinsic networks involved in value creation when an exchange happens (Vargo & Lusch, 2016b, p.49). A network is not only a network of resources but also of actors. It is a continuous process and a continuing connection among all the actors. When service becomes a "collaborative process", as suggested in S-D logic, RI happens through networks that connect multiple actors (Overkamp, Johan, Rodrigues, Arvola, & Holmlid, 2018). The value creation process that happens through these networks are coordinated and facilitated through certain socio-economic mechanisms (Overkamp et al., 2018).

Each actor provides certain resources or will collect or integrate a few of them. No actor alone provides value but only "potential value" (Overkamp et al., 2018). A simple example of this is when a manufacturer of a certain vehicle does not provide value when he/she sells a vehicle but only "potential value of transport" (Overkamp et al., 2018, p.2). The real value is created only when someone uses the vehicle for transport and the prerequisites of this use may include the person having a driving license, the government building roads, the fuel company selling fuel, the family of the car user supporting him/her to drive and many more. Here it is clear that the ultimate value creator is the user of the vehicle including previously involved parties because it is his/her purpose to drive a car that made even the manufacturing of the vehicle possible (Overkamp, 2018, p.2). Also, in organizations, an IT department is basically responsible for managing technology and providing tools to support day-to-day activities. Its role is to provide training, configure resources, and provide access to users. The staff of the IT department, however, are not the end-users. Let's take an online shared calendar for example. This tool is a web application that allows one or more users to edit and share with other users, online access to a calendar providing a transparent overview of an employee's schedule. Such a tool has the potential to solve issues like overlapping meetings, managing meeting time and dates, etc. Installing, configuring and maintaining such a tool requires the IT department to allocate resources and provide training and support to users. However, the actual value of their efforts becomes realized only when the end-user uses the technology and tool provided.

RI has no precondition of ownership of the resource in order to successfully create value (Overkamp et al., 2018, p. 3). A person can use a vehicle like a bus by not owning it but just buying a ticket. It must be kept in mind in all cases, that value is, in the end, a beneficiary-defined proposition (Overkamp et al., 2018, p. 4). The RI process also must be meaningful with an understanding of all the organic connections involved between and among the actors as well as the resources. In that sense, one particular resource cannot be posited as linked with the creation of one specific value. The resources, in other words, are not pre-defined and pre-connected with values. It is in a certain socio-economic context of value co-creation that a resource becomes a resource for a certain value. This is why Lusch and Vargo (2014) observed, "…essentially, resources are not, they become" (p. 2).

Interaction, knowledge and the diversity of resources are considered as the key factors that influence RI (Bohm, 2017). For example, in the energy sector, Bohm (2017) pointed out the case of virtual power plants, where the S-D logic has paved the way to make the actors look at their resources in a different way and integrate them in a different manner. This resulted in energy manufacturing firms integrating their resources with technology and knowledge providers to co-create new values that integrate the energy concerns of the society as a whole.

Moreover, RI can be either emergent or summative (Peters, 2016). Emergent RI results in value creation that is more than the total sum of the resource values and is called heteropathic RI (Peters, 2016). The summative kind of RI creates a value that is the total sum of the values of the resources which is labelled homeopathic RI (Peters, 2016). A service ecosystem is where "actors not only exercise their individual agency but also coordinate their actions to improve RI and mutual value creation" (Vargo & Lusch, 2018). This is why it is observed that "feedback and coordination" are the two basic factors that help one understand RI (Vargo & Lusch, 2018). Value co-creation happens within service ecosystems and this necessarily happens through RI (Vargo and Lusch, 2018). A simple example that Peters (2016) gives for homeopathic RI is that irrespective of whether one eats a fruit salad by eating apple pieces first or intermittently to melon pieces, the nutrition that one gets is the same. However, Peters (2016) pointed out, when oxygen and hydrogen combine to form water, the value created in the end is different from the values of each resource that existed before water was made. Within S-D logic, resources do not have an intrinsic value; they need application and integration to become valuable. Value creation therefore occurs 'when a potential resource is turned into a specific benefit' (Lusch et al. 2008 p. 8). Similarly, in IS research, the adoption

and use of IS resources have been the focus of many studies (Dwivedi, Rana, Jeyaraj, Clement, & Williams, 2019; Taherdoost, 2018). The importance of such a research stream lies under the idea that IS resources create value only when used by users and the overall value is greater than the sum of the components that have generated it. A very simple example is the use of a BA system in insight generation where using personal competencies (such as business knowledge and technical expertise) a user engages with BA resources to generate insights leading to informed decisions and then actions. The value of the insights generated and their potential outcome are different from the value of personal competencies and BA resources alone.

3.3 The Use of S-D logic in IS Research

Research on IT and services has a long history since the late 80s with Barras (1986) seminal work on the role of IT in service innovation, up to more recently on service innovation in a digital age (Barrett, Davidson, Prabhu, & Vargo, 2015). Even though many studies have provided many contributions to this research stream, still the argument that developing a better understanding of the role of IT in services is still important and considered a key priority for the emerging field of service science (Maglio & Breidbach, 2014; Ostrom, Parasuraman, Bowen, Patrício, & Voss, 2015) and in IS research as well (Maglio & Breidbach, 2014; Rai & Sambamurthy, 2006). Barrett et al. (2015) argued that the "goods-centric" mindset that is largely firm-centric, output-oriented and provides only implicit assumptions about service itself has put a limitation on IS scholars which pressed them to adopt a rather different approach to answer their inquiries, namely S-D logic. Through the conceptualization of service as a value co-creation processes that basically depends on resource integration and interactions involving the application of the actor competences for self-benefit or the benefit of another (Vargo & Lusch, 2016b), S-D logic has provided IS researchers with the necessary tools to develop new theoretical insights about service systems, their configurations, and interactions with resources (Maglio & Spohrer, 2008).

S-D logic has strong connections to IS research and has been used for analytical work in several IS studies. In fact, IS discipline was amongst the first to adopt S-D logic (Demirkan et al., 2008; Machamer, Darden, & Craver, 2000) and was found to be most used by IS scholars compared to other fields excluding marketing. It has been mainly used to extend IS research by placing service and service metaphors as core aspects of the field and considered as the

'philosophical foundation for service science' (Maglio & Spohrer, 2008, p. 18).

For example, Yan, Ye, Wang, and Hua (2010) have discussed service-oriented architecture (SOA) and service-dominant logic based on the strategic alignment model. Also, Lusch and Nambisan (2015) have developed a broadened view of service innovation based on S-D logic and offer a tripartite framework of service innovation consisting of service ecosystem, service platform and value co-creation. SD logic informed studies exploring the role of IT in service innovation (Breidbach & Maglio, 2015), self-service technologies (Scherer et al., 2015), or those developing reference models for product-service systems (Becker, Beverungen, & Knackstedt, 2010). Moreover, H.-M. Chen, Schütz, Kazman, and Matthes (2017), pointed to the importance of S-D logic in developing Lufthansa a new service centred business model to generate value from big data. This example is of special importance as it builds on S-D logic functional premises or axioms to improve their DSS and decision making regarding how to better personalize the customer experience, handle irregular situations, predict departure delays, and implement predictive and preventive aircraft maintenance.

The use of S-D logic in IS studies is still in its infancy but promises a great potential. S-D logic emphasizes the application of specialized competence through deeds, processes, and performance for a shared benefit between actors or only the actor itself (Vargo & Lusch, 2004). In other words, applying resources for one's own benefit or for others. This kind of mindset is valid in different settings such as business organizations, government organizations, households and individuals. However, it is especially consistent with the service concept in IT and IS such as in service computing including SOA and Software as Service (SaS) (Zhao, Tanniru, & Zhang, 2007). By portraying a system as a service system in IS, several benefits can be perceived as shown below (Alter, 2010).

1) It helps the IS field capture and exploit more of today's pervasive interest in services and the service economy.
2) It helps in focusing on the business value of IT because most internally directed systems within organizations basically perform services for other parts of the organization.
3) It improves the extent and quality of user participation because issues and details about services are easier to discuss than issues and details about what business professionals perceive as technical artefacts. In particular, the vocabulary of services would help point the discussion toward business issues.

4) It enriches systems analysis methods by introducing concepts that otherwise would be ignored or considered outside the legitimate scope of the analysis.

Point two specifically targets the internal organizational environment and claims that by perceiving internal systems as service systems, it elevates the idea that different parts of the organization mainly service each other. For example, the marketing department targets customers with product and service awareness campaigns which paves the way for the sales department to close deals and generate income which in turn is managed by the financial department. In such an example, the role of the IT department is crucial as it provides and manages the IT infrastructure that enables the overall process. This view is in line with S-D logic conceptualization of service as a value co-creation process that views the service system as an ecosystem of resource integrating actors collaborating and interacting to co-create value.

Even though S-D logic provides an interesting opportunity to investigate some phenomena in IS research, it has not been yet exploited what can be seen from the number of studies associated with S-D logic, especially those studies that are related to the DSS field which heavily relies on technology that constantly advances to accommodate users' needs. With the increased people IT literacy, DSS such as BA becomes more ubiquitous and pervasive in organizations and by looking at DSS from a service system perspective researcher in this field might not only contribute to the DSS field but also uncover some interesting findings related to how value is generated from such systems.

3.3.1 Service Dominant logic as a Theoretical Lens

A lens is a physical object (made of glass or other material) that can concentrate or disperse light rays used to examine something (Stevenson, 2010). Following the same metaphor, in academia a theoretical lens is a mechanism, perspective or even a viewpoint of which researchers examine a certain phenomenon, to highlight a particular aspect or develop some kind of mapping between elements of a specific domain (Niederman & March, 2019). We must understand that the lens is not necessarily a theory but it is rather the procedure we use to contribute to theorizing by either using a theory to observe a certain phenomenon and explain it, using a theory to highlight a specific element of the phenomenon or using the theory to focus on a specific element and ignore others (Niederman & March, 2019).

The rationale behind adopting S-D logic as a theoretical lens is contingent upon two notions. First, this dissertation depicts SSBA as an approach to data analytics enabled by a service environment consisting of different resources that facilitate the business user's independence in insight generation. Along the same line, the S-D logic theoretical lens provides a high-level description on how actors co-create value through resource integration and service exchange controlled and enabled by institutions within an ecosystem. This dissertation sees insight generation in SSBA and value co-creation in S-D logic analogous. This is due to the fact that the technical department enables the SSBA environment including the needed resources to generate insights from data. Consequently, the user (actor) in an SSBA environment uses personal competencies (resources) to interact with other resources and co-create the desired outcome and generate value. Both technical department and users have different roles but still co-create the service provided together for which S-D logic calls value co-creation in a service environment.

Second, S-D logic has been informed by several meta-theories such as institutional theory, system theory, and complexity theory and complexity economics. This dissertation is aware of the usefulness of other theories in exploring the investigated phenomenon such as institutional theory and its derivatives to potentially provide a good lens to understand institutions (Lawrence, Suddaby, & Leca, 2009) within an SSBA environment and how the norms, routines and social structures within an organization enable and control the process of insight generation. Moreover, the Resource Based View (RBV) of the firm provides a theoretical framework to understand how resources within an organization affect its general performance and why firms differ in their performance (Rumelt & Lamb, 1997). RBV potentially relates to how the resources in the SSBA environment, including users' competencies, facilitate the process of exploring data for insights, and ultimately affects other firm performance through more informed decision-making. However, RBV has its focus on the firm performance itself and not the actor within the firm. Also, RBV explores more of the roots of a competitive advantage within a firm and not how resources are integrated together to co-create value and promoting a competitive advantage. In short, the level of analysis in RBV is basically the firm and the network of firms. However, S-D logic provides a promising lens for exploring a phenomenon that includes resources provided as a service, users (actors), institutions and the concept of value co-creation at both an organizational and individual level (Brust, Breidbach, Antons, & Salge, 2017).

S-D logic is built upon five basic axioms, which represent important key concepts in this dissertation. The five axioms (which are discussed in section

0) and the service ecosystems perspective help to communicate the S-D logic key ideas of value co-creation. S-D logic view (sometimes referred to it as narrative) is iterative over time as actors integrate resources and co-create value through "holistic, meaning-laden experiences in nested and overlapping service ecosystems, governed and evaluated through their institutional arrangements" (Vargo & Lusch, 2016a, p. 7).

As has been discussed, SSBA represents an approach to BA where a user is surrounded by a multitude of tools and technologies considered as resources. Using personal resources or competencies (skills, knowledge, motivation, etc.), the user engages in resource integration activities to solve an analytical task. The outcome of this process are the insights developed from data and represents the value generated.

S-D logic provides a high-level description of the fundamental elements or attributes associated with SSBA. The axioms presented in section 0 serve as the basis for describing and explaining the self-service approach to BA from a service perspective and the general activities that a user engages in to produce value. To further elaborate, let us assume the following hypothetical scenario. An organization decides that being more data-driven in decision-making is a key competitive advantage. The IT/BI department provides, configures and manages tools and technologies that supports SSBA (such as Tableau, Adobe Analytics and QlikSense). In their turn, the employees (actors) approach this setup and engage with the resources the IT/BI department provides (environment) with a self-service mindset. In Table 7 a mapping between S-D logic axioms and SSBA is described. Third, S-D logic emphasizes the system thinking in co-creating value. It highlights the importance of the service ecosystem and its impact on the value co-creation. This is of special importance as SSBA is enabled by an environment that supports user collaboration, interaction with resources and independence in data analytics. The system thinking in this context provides an integrated view of all the microelements connected in the SSBA environment to generate the intended value which later becomes a part of the environment itself.

Table 7:
S-D logic axiom in SSBA context (adapted from (Vargo & Lusch, 2016a))

	S-D logic Axiom	In SSBA context	Practical example
Axiom 1	Service is the fundamental basis of exchange.	Service (the availability of data and analytical tools, support) is at the core of SSBA.	SSBA approach enables access to clean and integrated data models, technological tools, processes to generate insights. This service developed, configured and enabled by the cooperation between techno-oriented and business employees.
Axiom 2	Value is co-created by multiple actors, always including the beneficiary.	Users in SSBA (also the beneficiary) engage in a co-creation process (supported by other employees) to generate the required insight for the goal of solving an analytical task.	The employee accesses and interacts with the data using personal capabilities to process data into insight. As this process is not trivial, support from both techno-oriented and business personal is provided.
Axiom 3	All social and economic actors are resource integrators.	SSBA users and management, IT/BI personnel are all actors integrating their resources to enable value generation.	In the self-service approach to BA, all stakeholders contribute in enabling and sustaining SSBA. Organization provides vision and strategy, business employees provide experience and understanding of the business and techno-oriented employees provide technical skills and capabilities. All those resources merge together to enable and sustain SSBA.
Axiom 4	Value is always uniquely and phenomenologically determined by the beneficiary.	The generated outcome in SSBA is the insight developed which is used in decision-making and actions. It follows that the decision maker is the beneficiary who determines whether his self-service approach to BA is of value.	After the user generates insights to solve a problem or address an opportunity, it deems only logical that he determines the value of his efforts.
Axiom 5	Value co-creation is coordinated through actor-generated institutions and institutional arrangements.	SSBA is an approach that involves the coordination between the user's institutions (norms, values, ideology) and cognitive skills together with the organization settings and rules.	Institutions like motivation, skills, values, willingness to be in control and autonomous in insight generation have great effect on the generated value. Also, organizational institution such as the routines, processes, vision affect SSBA environment.

3.4 Concluding Remarks

S-D logic describes the value co-creation occurring among a configuration of actors integrating resources in a self-contained and self-adjusting environment referred to as a service environment. The concept of resource integration in S-D logic depicts an activity between actors' competencies and other resources in a service environment to generate a value unique to its beneficiary. This goes hand in hand with the concept of data analytics whereby a user engages technologies to process data and draw conclusions or to develop certain insights to support decision making and action-taking. As such, S-D logic provides an appropriate basis to explore and describes BA especially by the self-service approach to BA. This dissertation uses the conceptualization of how value is co-created through resource integration activities controlled by institutions within a service system. The system thinking of S-D logic provides an interesting perspective to understand the network of activities that connects different resource integrating actors to generate the foreseen value.

4 Research Approach and Design

The aim of this chapter is to present the arguments behind the interpretive case study research design choice of this dissertation. Although each appended paper includes a method section describing the research settings, interviews, and data analyses, still no detailed description is provided due to the publishing outlet space limitation. As such, this chapter presents a more detailed explanation of the research paradigm, methods used, and data analysis adopted in both research phases over the course of this dissertation.

This chapter is structured as follow. First, the research approach is discussed in connection with the study context. Then the research design is presented and the rationale behind adopting a case study is discussed followed by a presentation of the case and how such a case is considered a good context in relation to the general aim of this dissertation. Next, the research process is described through an integrated model of both empirical phases. Then, data collection and analysis are elaborated in two separate sections. Finally, ethical considerations are presented including informed consent, confidentiality and a non-disclosure agreement.

4.1 Research Approach

This research focuses on describing and explaining the phenomenon of SSBA in organizations. The main aim of the research is to investigate how business users develop insights in an SSBA environment. To achieve this aim, a qualitative approach was deemed fruitful as will be shown in this section.

Qualitative research can be conducted through different research philosophies such as positivist, interpretive or critical (Klein & Myers, 1999; Myers & Avison, 2002). Klein and Myers (1999) describes the three philosophical perspectives in IS research as follows:

Positivist, *"if there is evidence of formal propositions, quantifiable measures*

of variables, hypothesis testing, and the drawing of inferences about a phenomenon from a representative sample to a stated population."

Interpretive, "if it is assumed that our knowledge of reality is gained only through social constructions such a language, consciousness, shared meanings, documents, tools, and other artifacts."

Critical, "if the main task is seen as being one of social critique, whereby the restrictive and alienating conditions of the status quo are brought to light. Critical research seeks to be emancipatory in that it aims to help eliminate the causes of unwarranted alienation and domination and thereby enhance the opportunities for realizing human potential"

(Klein & Myers, 1999, p. 69)

An interpretive approach accepts the critical view that the world is socially constructed, yet shares the positivist belief of the researcher as an observer. In contrast, interpretive research follows several of the research traditions established in anthropology, such as the provision of thick descriptions, which permit a deeper understanding of a given phenomenon (Walsham, 1995). Interpretive research in IS is dominantly associated with case studies, action research, and ethnographies (Walsham, 2006). Regardless of the type of methodology, the basic assumption in interpretive research is the researcher's involvement in the study, ranging from passive observation to intentional action. In fact, the researcher's involvement in fieldwork is the principal aim for collecting data that is used for interpretive analysis.

In this dissertation, a qualitative interpretive perspective is adopted due to its usefulness in exploring socio-technological phenomena and gaining a deep understanding from the viewpoint of the participants in their real environment (Kaplan & Maxwell, 2005). It is also valuable in exploring and describing the specific context by which participants act (Maxwell, 2008). According to Orlikowski and Baroudi (1991) "… social processes can be usefully studied with an interpretive perspective, which is explicitly designed to capture complex, dynamic, social phenomena that are both context and time dependent. (p. 18)". In an SSBA context, the main promise and goal the organization aims to achieve is co-created between different employees (either technical or business) and is considered a social process involving the use of many resources coined as resource integration. This social process is both time and environment dependent since the need to develop insights from data is

mainly associated with addressing a specific decision problem or a business opportunity. The nature of this research, with its pursuit of understanding the connections and interactions among the actors, resources, and the environment, all of which constitute different parts of a social reality, point to an interpretive perspective. This is in line with the aim of this research as the starting point for exploring and describing the nature of SSBA and how resources are integrated to generate value.

The interpretive perspective points to the fact that knowledge of reality, which includes the domain of human actions, is socially constructed. The role of the researcher is to examine the phenomenon of interest in its natural setting from the participants' perspectives. This is of special importance as technology plays a large and fundamental role in this research especially when exploring the interplay between resources and users in the SSBA environment. In an effort to aid researchers during their field studies, Klein and Myers (1999) have developed seven principles or guidelines for conducting and evaluating interpretive IS field research (including case studies) as shown below. The seven guidelines not only target researchers and try to guide them in doing interpretive research but also targets reviewers by trying to provide a tool to help in assessing interpretive research.

1. **The Fundamental Principle of the Hermeneutic Circle**: This principle suggests that all human understanding is achieved by iterating between considering the interdependent meaning of parts and the whole that they form. This principle of human understanding is fundamental to all the other principles.
2. **The Principle of Contextualization:** Requires critical reflection of the social and historical background of the research setting, so that the intended audience can see how the current situation under investigation emerged.
3. **The Principle of Interaction Between the Researchers and the Subjects:** Requires critical reflection on how the research materials (or "data") were socially constructed through the interaction between the researchers and participants.
4. **The Principle of Abstraction and Generalization:** Requires relating the idiographic details revealed by the data interpretation through the application of principles one and two to theoretical, general concepts that describe the nature of human understanding and social action.

5. **The Principle of Dialogical Reasoning:** Requires sensitivity to possible contradictions between the theoretical preconceptions guiding the research design and actual findings ("the story which the data tells") with subsequent cycles of revision.
6. **The Principle of Multiple Interpretations:** Requires sensitivity to possible differences in interpretations among the participants as are typically expressed in multiple narratives or stories of the same sequence of events under study. Similar to multiple witness accounts even if all tell it as they saw it.
7. **The Principle of Suspicion:** Requires sensitivity to possible "biases" and systematic "distortions" in the narratives collected from the participants.

Yet the nature of interpretive studies is highly influenced by the diversity and context-dependent settings and may affect the applicability of having a specific set of criteria guiding field works, however, this does not imply that we cannot have a standard by which we conduct and judge interpretive research.

4.1.1   Case Study Research Design

The nature of case study research and the range of its research alternatives make it highly convenient for researchers in general and IS researchers in particular. For example, it is used in the positivist (Cavaye, 1996) and interpretivist philosophical traditions (Carroll & Swatman, 2000; Walsham, 1995), and also for theory testing (Robitscher, 1972) or theory building (Atkins & Sampson, 2002) through qualitative or mixed methods (Cavaye, 1996; Walsham, 1995; Yin, 2009). As such, this thesis adopts case study as research inquiry to investigate SSBA in organizations.

Yin (2013, p.16) defines a case study as "an empirical inquiry that investigates a contemporary phenomenon in depth and within its real-world context, especially when the boundaries between phenomenon and context may not be clearly evident". The definition of Yin (2013) highlights three major components of a case study: contemporary phenomenon, real-world context, and vague boundaries between the phenomenon and its context. He further discusses the rationale behind adopting case study research as method of inquiry (see Table 8). Even though Yin (1989) adopts a positivist stance while describing the case study research, still he acknowledges the importance of 'how' and 'why' questions in the case study which is in line and acceptable to the interpretive stance.

Table 8:
Rational in adopting case study (Yin, 2009)

Rational	Description
Critical case	Used for testing a well-formulated theory
Extreme or unique case	To give more insights on a specific phenomenon
Representative case	Suitable for capturing the circumstances of typical situations
Revelatory case	The researcher has an opportunity to access, observe and analyse an inaccessible environment
Longitudinal case	For studying one particular case at various different points over time.

In connection to this study and based on Table 8, SSBA is a relatively new phenomenon being promoted by the industry expecting to create value to organizations in their specific context. The description of the selected case in Sections 4.2 and 4.4 provide insights on why this case is unique, representative and revelatory. The qualitative research allows exploring the research topic and subject in a detailed view so as to get a deeper understanding of the phenomenon (Creswell, Hanson, Clark Plano, & Morales, 2007) which is in line with the aim of this dissertation.

Generally, qualitative research and especially case studies equip researchers with a set of tools for conducting research when other approaches would be difficult, or would simply neglect important factors. For example, a laboratory-controlled experiment would be suitable to isolate a single variable or a specific aspect of a phenomenon, however it would extract it from its context and real-world environment, hence limiting insights and possibly impacting the results. In contrast, rather than isolating variables, qualitative research accepts the relative complexity and messiness of the real-world context by exploring multiple sources of data aiming to reduce the risk of unwarranted influence or bias from any single source (Klein & Myers, 1999).

4.2 Selection of The Case

The selection of the data collection site is an important element of any research. Many aspects and characteristics should be considered when choosing a case to study. Examples of organizational characteristics are size, organizational structure, private or public ownership, geographical coverage, and so on. Furthermore, Yin (2009) has developed a set of factors to be considered when

choosing a case to study (see Table 8) which shows the importance of choosing a good case to study and its impact on the outcome.

It is also important to consider the nature of business and technology employed to facilitate business processes. In accordance with the aim of this dissertation, the target organization should have a (1) data intensive environment, and (2) be technology driven, and (3) have a data driven ideology supported by the top management to enable employees to engage in self-service analytical task solving activities.

A Digital Marketplace (DM) is an illustrative example of a data intensive environment driven by technology mainly its digital platform. In a DM, service exchange is facilitated through information repackaging and innovation. A digital marketplace is an ecosystem of several participants interacting together for a shared benefit (Rysman, 2009). Parties such as buyers, sellers and market intermediaries (Bakos, 1998) use a digital platform and a service provided by the digital marketplace. This results in an abundant amount of data in the form of clickstreams and data logs. Such data sources contain hidden information that can be leveraged to optimize the digital platform and provide insights into user needs and behaviours, hence coping with the changing nature of the service provided. An example of such leverage would be to uncover users' browsing and purchasing behaviours and patterns (H. Chen et al., 2012) – various analytical tools can be used to create a trail of the users' online activities – to deliver a more customized and personalized service with the help of users clickstream analysis. Such data-intensive environments are characterized by rapid and uncertain changes that constitute the foundation for an innovation-driven economy (El Sawy, Malhotra, Park, & Pavlou, 2010). Hence, a digital marketplace fits the target profile and is considered a case of choice.

The empirical data was collected at Finn.no, the top digital marketplace in Norway. Finn.no was founded in 1996 focusing on classified advertisements but with a great vision. Today, Finn.no is not only a digital marketplace where buyers and sellers use the company's digital platform to find a common ground to perform transactions, but it has also expanded its service offerings to include: providing statistics about real estate, monetary statistics on vacation rentals, statistics about population clusters and concentration in specific areas and to include different parties such as governments, newspapers, students and research labs.

It is important to mention that Finn.no belongs to a larger organization called "Schibsted Media Group". Schibsted is an international company of digital consumer brands with over 5,000 employees. It has activities in several areas including marketplaces and digital services that empower consumers through which millions of people interact with Schibsted companies every day. Schibsted owns over 80 digital marketplaces in Scandinavia and worldwide with a global strategy emphasizing the collaboration between employees and the adoption of data driven technologies. Finn.no is one of the most innovative and data driven companies within Schibsted in Scandinavia, which makes it a critical and representative case to study.

Finn.no has become a central data repository for different agencies (private and governmental) as they constantly send requests regarding various statistical analyses and ad-hoc reports. In addition, high profile sellers request reports from marketing and sales departments with regards to their advertisement reach and investment values.

Finn.no has grown to an extent that the huge number of requests originating from different parties has overwhelmed the IT/BI department. As a response to this situation, in 2010 Finn.no management decided building a more agile and data-driven organization to create a first-line response to such requests by empowering business users with access to data and technology. This enabled a self-service environment within the organization. In other words, Finn.no has included in their strategic vision the concept of 'data in the spine', which is a metaphor for data democratization or data analytics decentralization. This vision entails that business users should have the capacity to explore data, analyse it and make operational decisions without referring to the IT/BI department, which created a first-line response.

This vision makes Finn.no more agile through two dimensions: market capitalizing agility and operational adjustment agility (Lu & Ramamurthy, 2011). Market capitalizing agility refers to a firm's ability to constantly look for areas to improve upon in their offered product or service and leverage on these to meet ever-changing customer needs. Operational adjustment agility, on the other hand, refers to a firm's ability to address their inner workings – distributed responsibility, data ownership and transparency across organizational units, etc. – as a foundation for responding to external changes.

For that purpose, a self-service approach to business analytics has been adopted with the aim of augmenting employees' capability and agility in answering requests from external customers together with fulfilling their own

needs in terms of data analysis, making Finn.no an ideal subject for our investigation. What is still unclear is how the SSBA environment enables such agility and how employees engage with data to develop the needed insights to make an informed decision. In other words, '***How do business users develop insight in an SSBA environment***'?

4.3 Research Process

The research design follows two consecutive phases as a process of inquiry (see Figure 6). Each phase provides input for the next one moving from a broad perspective to a narrower and more specific one. That is from comparing the SSBA phenomenon and its environment to a specific explanation of the resource integration patterns and the associated implications.
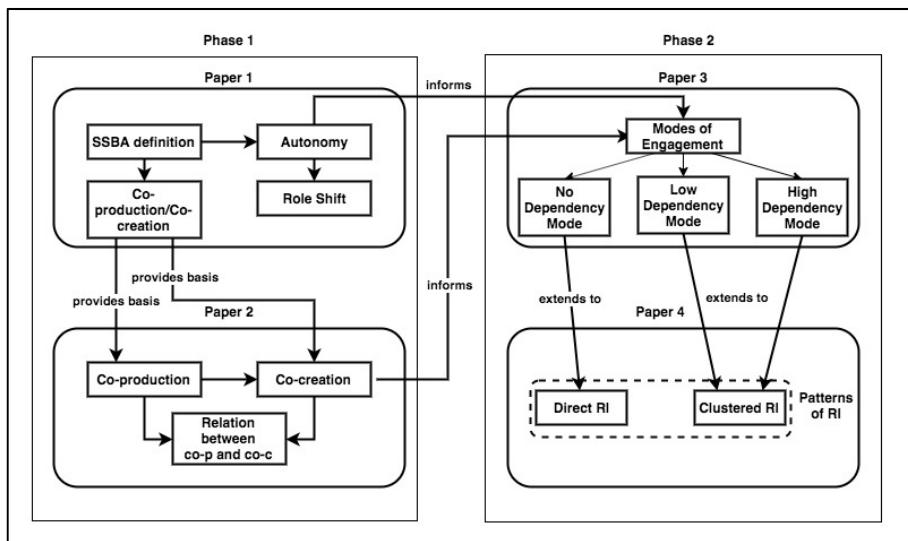
Figure 6:
Phases of research inquiry

The first phase starts by exploring the phenomenon of SSBA to understand its magnitude and generate initial ideas about the self-service approach to BA. This phase also helps in uncovering any potential issue this approach may have in permitting more in-depth analysis of a particular aspect of SSBA

(Bhattacherjee, 2012). This phase is divided into two main parts. Part 1, through a systematic literature review (Vom Brocke et al., 2009) of an 81-journal article on Self-Service Technologies (SST) (see Figure 7, for more information see Paper 1), the aim is to provide more understanding on the nature of the self-service aspect and its potential impact on users (in our case employees). This part is of importance as it explores previous literature on SST and connects it to BA by providing a grounded description of SSBA, characteristics and potential outcomes to its users. As such, this part serves as a basis for both phases and provides potential research directions for the phenomenon of interest.
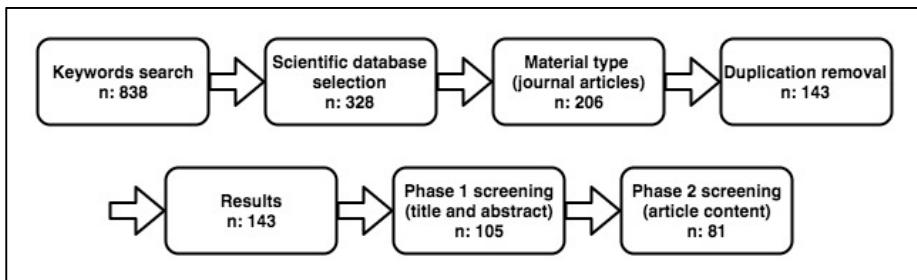
Figure 7:
Process of literature review

In Part 2, an empirical investigation is carried out to provide a focused insight on the nature of SSBA and what really enables such an approach to data analytics. In this part, the focus is given to the process of enabling the SSBA environment and the role of the stakeholders involved. It provides a high-level model illustrating the positive relationship between both phases (co-production and co-creation) and the overall value generated, which is data insights in our case reported in Bani-Hani, Pareigis, Tona, and Carlsson (2018) (see Paper 2).

The Second phase has more emphasis on the user engagement during insight generation and the process of RI in an SSBA environment. This phase is also divided into two main parts. The first builds on the finding of Paper 2 and investigates the modes of engagement occurring during the co-creation phase considering that the main premise of SSBA is the autonomy of the users (see Paper 3). This part mainly focuses on describing No Dependency Mode (NDM), Low Dependency Mode (LDM) and High Dependency Mode (HDM). The second part focuses on resource integration patterns and enactments of resources in an SSBA environment and how those enactments generate the

desired value. It empirically describes the interaction configurations occurring in such an environment and how those interactions lead to value generation (see Paper 4).

Both phases are directly related to the research questions and collectively fulfil the aim of this dissertation. During the research process, a fifth paper has emerged from the empirical data that has no direct relation to either research questions, however the finding of the fifth paper still has important contributions in terms of how SSBA impacts the organization's agility in responding to internal and external needs and provide competitive advantage which in turn is considered as organizational value (see Paper 5).

4.4 Methods of Data Collection

There are several sources of evidence and data collection methods the researcher can employ to investigate a phenomenon or answer a research question. The value of each data collection method is dependent on the context, the goal of the research, and many other factors. Many scholars have published journal articles and book chapters trying to classify these methods and provide guidelines of when and where to use a specific method. For example, interviews are best when seeking to provide a deeper understanding of a specific phenomenon (Kvale, 2008). Observation, on the other hand, is known to be good at understanding the activities of participants in real settings (Denzin & Lincoln, 2005). Also, focus groups have been used in situations where the interaction between different participants is important and may reveal some hidden tension or discussion on the research topic (Yin, 2015). Sometimes neither interviews nor observation can reveal what documents do as they contain unspoken or hidden rules, regulations, events, and any other information that could be critically valuable for research (Neuman, 2013). This dissertation adopts mainly three sources of evidence to collect empirical data namely: interviews, observations and organization documents with more focus on interviews.

4.4.1 Interviews

The interview technique has been extensively used in multiple disciplines including IS. It is considered appropriate when there is a need to gather nuanced data and data when the context is important (Schultze & Avital, 2011), e.g. organizational environment or SSBA users' behaviour.

To gain a comprehensive understanding, participants holding different positions in different departments have been be selected at Finn.no. The selection of participants was based on a snowball sampling strategy (Biernacki & Waldorf, 1981) in an effort to capitalize the expert experience within the organization and provide a starting point for the interviews. It is also valuable in studies that are somehow outside the academic mainstream which is our case. Each participant pointed out other potential participants explicitly or implicitly through drawing "mock-ups" explaining the role of data in communicating with different employees (see *Figure 8*).
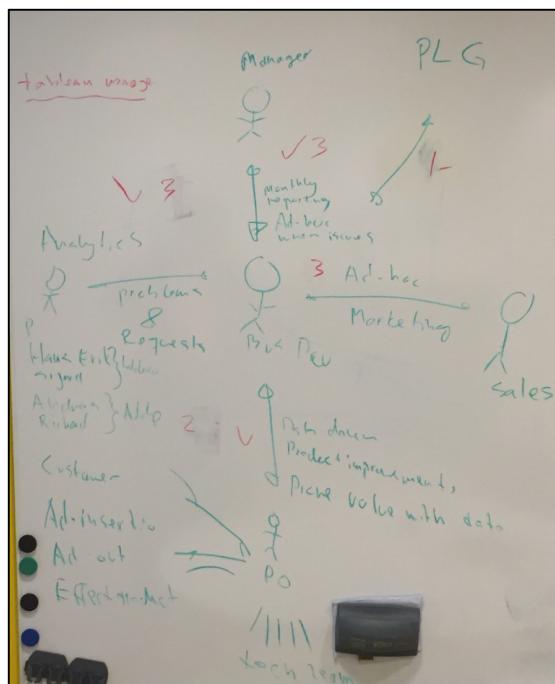
Figure 8:
A mockup drawing example of a business developer.

The mock-up drawings brought more description and can even encourage participants to be more engaged during the interview by providing more information of the role of SSBA in their daily work.

A total of 22 interviews were conducted with employees at different positions in the organization. The interviews lasted between 30 min to 3 hours depending on the position, responsibilities and involvement with data analysis. Confidentiality was maintained by not disclosing the name, age, gender and detailed position in the organization. To minimize the bias and influence of the interviewer in collecting data, interviews were recorded (with the consent of the participant) and transcribed verbatim and sent later to the participant together with the notes taken during the interviews for validation (Silverman, 2016).

Table 9:
First round of interviews

Participant	Year	Medium	Duration (Min)	Motivation
Public Relations and Comm.	2016	Face to face	30	Engagement in SSBA
Business Developer	2016	Face to face	50	Provide input on how problem or opportunity is formulized. When and how data is accessed. How data is analysed. How self-service is perceived. Types of resources involved while generating insights.
Business Developer	2016	Face to face	105	
Market Advisor	2016	Face to face	45	Engagement in SSBA
CFO	2016	Face to face	60	Organizational strategies to enable SSBA environment. Strategies to promote SSBA.
Sales Project Manager	2016	Face to face	105	Engagement in SSBA
Market Researcher	2016	Face to face	60	Engagement in SSBA
Market Researcher	2016	Face to face	30	
Senior Analyst	2016	Face to face	40	Value of SSBA from IT/BI department perspective. Input into how users engage with tools and technologies
Senior Analyst	2016	Face to face	180 (3 sessions)	
Senior Analyst	2016	Face to face	60	
Senior Insight Interpreter	2016	Face to face	70	Level of support users need during insight generation.
Senior Insight Interpreter	2016	Face to face	40	
		Total	14:36 hours	

The interviews were carried out at different points in time over 3 years. The first round of interviews was conducted in 2016 with 13 employees as shown

in Table 9. The first round of interviews was important as it provided a deeper understanding of the context, the importance of data in daily activities, the routines, line of business and products and the history behind adopting a self-service approach to data analytics.

The second round of interviews was held during late 2017 and 2018 with 9 participants. At this phase, interviews had a more specific nature and theme based on the theoretical lens adopted (see Chapter 3). The majority of participants were in the product development department as the self-service approach was critical for their work-related tasks. Since they were responsible for developing the different products the organization provides for its customers, mainly using data, independence, control, and autonomy was a key factor in this department.

Table 10:
Second round of interviews

Participant	Year	Medium	Duration (Min)	Motivation
Senior Insight Interpreter	2017	Skype	45	Provide insight on the technology provided to users.
Senior Insight Interpreter	2017	Skype	35	Provide insights on data models provided to users.
Acting head of Insights	2017	Skype	53	Provides insights on general support strategies
Business Development	2018	Face to face	62	Provide input on how problem or opportunity is formulized.
Business Development	2018	Face to face	71	When and how data is accessed. How data is analysed.
Business Development	2018	Face to face	58	How self-service is perceived. Types of resources involved while
Business Development	2018	Face to face	61	generating insights.
Business Development	2018	Face to face	55	
Human Resources	2018	Face to face	45	How new employees are selected (ideologies, culture and behaviour)
		Total	8 hours	

All interviews started with a short description of the research topic, a background about the interviewer, confidentiality and ethical consent signing and a request for audio recording the interview (see interview guide and other documents in appendix). The interviews in the second round were also transcribed and sent to the participants for validation.

In interpretive research, the researcher is considered to be a part of the social phenomenon under investigation. The challenge is to assume a neutral position and avoid any bias when interviewing participants. This was critical since before starting my Ph.D., I was working as a business intelligence specialist including how to improve user engagement in data analytics. My challenge was to use my previous practical experience not to steer the interview discussion but to understand the context of the participant and the interaction occurring with technology and with other employees. This was difficult to achieve as we are all biased by our background, knowledge, and experience (Walsham, 2006). However, since I maintained a neutral position and was not aligned with a particular technology, system or process helped me to be less subjective. Since SSBA and its environment was not new to me, and I had my fair share of experience, I used techniques like drawing, practical examples, and informal talks during lunch and breaks to collect as much information as possible and identify the key employees involved with SSBA.

4.4.2   Observations

Observation is an invaluable data collection method especially when it comes to new technology or phenomenon because it assists in understanding the actual use and any issues with the technology within its context (Yin, 2013). Also, it provides a way of validating and complementing the interviews (Silverman, 2016). From an SSBA perspective, observing a user can bring some insights which interviews cannot always capture. For example, while observing participants, I paid particular attention to the tools being used when solving an analytical task, when or at what stage the user required extra help and support, and how the user dealt with pressure when making a decision based on data analytics. Observation was also an opportunity to see if there are different levels of self-service and whether it is mainly related to the position in the organization or if it is an overall ideology in the organization.

The observation sessions took place at the same time period as the interviews. That is after each interview, the participant and I agreed to keep an open communication channel in order to specify a day for the observation. Since the aim was to observe how the employee interacted with data and generate insights, the challenge was to follow a business problem or opportunity from start till end. Therefore, I asked the participant to notify me of any relevant information that may be of importance. Having the observation sessions after the interviews made things easier for both parties. The interviews acted as an

icebreaker and created familiarity between participants, hence allowed informal conversation and made the participants feel more comfortable.

One major challenge during the observation sessions was how to capture information. Structured and instructive information was the best way to conduct observation studies, and how to take notes on what was observed was very diverse in the literature. There are no clear instructions as each setting is unique and has its own challenges therefore it is to some extent left to the researcher's judgment. Video recording is very useful in observation sessions (Bøllingtoft, 2007), however, that was not an option, as the participants did not feel comfortable being video recorded. Also, an audio recording was unrealistic due to the structure of the office space and the surrounding noise. As a result, the only remaining way to capture any interesting event or observation was through notes.

Table 11:
List of observation sessions

Observed	Location	Year	Duration (Min)	Observed event
Sales	Participant's office	2016	45	How a task is independently accomplished
Sales	Participant's office	2016	55	How a task is independently accomplished
Business Development	Participant's office	2016	101	How different resources are used to generate insight. The process of insight generation. When support is needed. What type of support is needed? What type of institutions are involved in the process of insight generation?
Business Development	Participant's office	2016	120	How different resources are used to generate insight. The process of insight generation. When support is needed. What type of support is needed? What type of institutions are involved in the process of insight generation?
Business Development	Participant's office	2016	51	
Business Development	Participant's office	2018	66	
Business Development	Participant's office	2018	25	

4.4.3   Documents

Organizational documents have been a core source of evidence in qualitative research for many years (Bowen, 2009). They have different forms and contents such as, but not limited to, advertisements, agendas, attendance registers, minutes of meetings, manuals, background papers, event programs, charts, application forms organizational reports, survey data (internal or

external), and various public records. As a result of the abundant amount of existing documents, it is important to exert good care in deciding which documents deserve attention and the amount of time devoted to their collection (Yin, 2015).

Document analysis is often used in combination with other qualitative research methods to corroborate findings or "triangulation" —'the combination of methodologies in the study of the same phenomenon' or a combination of data sources (Denzin, 1970, p. 291). For example, internal memos and email regarding the update of a data model serving SSBA informs this research that technical support is needed and therefore used. Also, survey results within the organization may inform this research on certain aspects of SSBA in terms of setup, engagement, and support. For example, a survey conducted by the technical department at the investigated organization aimed at classifying the self-served users into categories based on their competencies in data analytics (see Table 12 for the list of documents).

Table 12:
List of documents

Source	Category	Content description	Motivation
Head of insights	Technical	Architecture of technology used and their data source	An overarching view of technology and type of data provided to users.
Head of insights	Technical	XML log files (tableau)	Cross-validate participant and their self-service activities
Head of insights	Technical	Export of user activities of SS tools	Cross-validate participant and their self-service activities
Business Developer	Management	Organizational structure chart	
Business Developer	Policies	Internal routines for problem solving	Routines and guidelines within the organization (institutions)
Head of insights	Management	Internal surveys	Competencies of users (capabilities to engage with resources to generate insights)
Business Development	Participant office	Problem solving cases	Provided a real example on solved cases.

29 interviews were conducted with the business development department employees and the report included a rating for each employee to help in the classification. In doing so, the technical department was more informed about the maturity of this department in terms of self-service. Those results have informed this research regarding, which group needed more supports, and

which was more independent, the overall competencies needed to perform data analytics and the technical resources (technology) present in the SSBA environment. Generally, documents are used to supplement data from interviews and observations and give better context on certain processes and routines.

4.4.4   Data Triangulation

The use of multiple data sources is a major strength of case study research (Eisenhardt, 1989; Yin, 2009). Data triangulation is the process in which a researcher attempts to use multiple data sources about the phenomena under investigation (Patton, 1999). It is claimed that data triangulation permits researchers to address a wider range of behavioural, historical and attitudinal events (Yin, 2009, 2013). In addition, data triangulation maintains the development of converging lines of inquiry and increases the validity of the collected data (Yin, 2009, 2013).

There exist four types of triangulation: method triangulation, investigator triangulation, theory triangulation, and data source triangulation (Denzin, 2017; Denzin & Lincoln, 2005; Patton, 1999). In this research, data source triangulation is adopted due to the limitation of resources such as several investigators working on the same project and time. The three previously mentioned data sources have been used in conjunction to develop more knowledge of SSBA. For example, in Paper 3, organization documents have been used to understand the technical capabilities the users possess to engage in a specific data analytics step. In turn, the interviews used this information to have a better understanding of the type of interaction happening and resource enacted. But to have a more realistic view, the observation provided real-time insight and the ability to validate the information provided through the interviews and uncover an aspect of the insight generation process that was not discovered (see Paper 4). A description of all data sources and motivations behind using them was presented in Tables 9, 10, 11 and 12.

4.5 Data Analysis

Based on the data collection technique this research employs, text data will be the major and dominant source of evidence. Therefore, it is important to use a data analysis technique that not only classifies and categorizes text based on language intensity and similar meaning, but goes beyond that (R. P. Weber, 1990). To analyse the data generated, this research uses the Miles, Huberman, and Saldana (2014) qualitative data analysis framework. This choice is guided by their conceptualization of qualitative data analysis, as they describe three concurrent flows of activities to extract knowledge from empirical material, which supports the idea of concurrency between the activities until findings are generated.

First, data condensation, which refers to "the process of selecting, focusing, simplifying, abstracting, and/or transforming the data that appear in the full corpus (body) of written-up field notes, interview transcripts, documents, and other empirical materials." (Miles et al., 2014, p. 31). They consider data condensation as a part of the analysis as it processes the empirical material by sharpening, sorting, discarding and organizing data in a way that makes drawing conclusions possible.

In this research, the process started in Paper 1 with a systematic literature review of SST and drawing parallels with SSBA to provide a grounded description of SSBA, characteristics and potential outcomes to its users. After applying the exclusion criteria, the selected articles resulted in 81 articles organized and analysed in an excel sheet and contained information about the author, discipline, publishing year, study context, the nature of the IT artefact, and how SST is perceived and contribution (see Figure 9).

Author/s	Published Year	Discipline	Research Method	Study Context	IT artifact	What is SST?	Contribution
Sergios Dimitriadis and Nikolaos Kyrezis	2011	Marketing and Communica	quantitative (questionn	SST adoption (technology acceptance variables, trusting beliefs and trusting intention)	Internet and phone banking	hardware and softwa	patterns of adoption are quite similar for the two channels but differ across transactions. Furthermore, the trusting intention has a strong mediating role between trusting beliefs and technology-acceptance variables on one hand, and intention to use these channels on the other hand
Ryan W. Buell, Dennis Campbell, and Frances X. Frei	2010	Production and Operations Management	quantitative (observation and transaction log)	Customer satisfaction and retention	ATMs, online bill payment, online banking, and IVR to be self-service channels	hardware and softwa	relative to face-to-face service, customers who use self-service channels for a greater proportion of their transactions are either no more satisfied, or less satisfied with the service they receive, depending on the channel. However, we also find that these same customers are predictably less likely to defect to a competitor if they are heavily reliant on self-service channels characterized by high switching costs. Through a mediation model, we demonstrate that, when self-service usage promotes retention, it does so in a way that is consistent with switching costs. As a robustness check, we examine the behavior of channel enthusiasts, who concentrate transactions among specific channels. Relative to more diversified customers, we find that self-service enthusiasts in low switching cost channels defect with greater frequency, while self-service enthusiasts in high switching cost channels are retained with greater frequency.
Joel E. Collier & Daniel L. Sherre	2010	Marketing Science	quantitative (survey)	SST usage intention (perceived control and convenience)	digital media entertainment provider	software	perceived control and convenience do impact the intentions of customers to use an SST in the futu
Michal Girman, Peter Keusch an	2009	Electrical Engineering, Mechatronics and Industrial Engineering	case study with quantitative contents	SST Effectiveness and availability	vending machine, payphone	hardware	SST providers should not count on failure reports by users and be proactive because it is better to correct faults before they lead to failures.
BRIAN R. KINARD, MICHAEL L. CAPELLA and JERRY L. KINARD	2009	Marketing	experimental testing and questionnaire	SST adoption from a customer behavior and social context (social influence)	self-service checkout systems	hardware and softwa	while boundary conditions regarding social size effects exist under which social impact theory does not hold, such effects appear to be moderated by the level of familiarity with the purchase-task situation.
JANET H. MARLER, SANDRA L. FISHER and WEILING KE	2009	Business	quantitative (printed su	employee user acceptance of SST (implementation)	Web-based employee self-service (ESS)	software	employees are more likely to intend to use ESS technology when they have positive attitudes toward using it and when subjective norms in the organization support use of the technology. Perceived organizational support (POS) enhanced the effect of managerial pressure on perceptions of normative beliefs supporting use of the technology post-implementation.

Figure 9:
Excerpt from the excel document

Informed by the literature review and the study context, the theoretical framework was chosen. S-D logic provides a high-level description of value co-creation through a cyclical process containing core components such as co-production, co-creation, RI, service exchange and institutions. Those components were used as initial labels for focusing and abstracting the empirical data. For example, in Paper 2 co-production and co-creation served as the basic codes (see appended Paper 2).

In this activity, this research was also inspired by the qualitative content analysis strategy when coding the interview transcripts. This strategy is valuable as it analyses text data with a special focus on the content or contextual meaning of the text (Forman & Damschroder, 2007). Hsieh and Shannon (2005) describe three types of content analysis: conventional, direct, and summative content analysis. The three types differ in the way data is coded. The conventional is more of inductive as the codes are emerging from the data after repeatedly reading the transcripts of interviews. The direct has a deductive nature where theory is used as an analytical lens and the codes are based on it. The summative content analysis uses the frequency of some certain words in the data and describes it qualitatively (for more details on the process of each type please refer to Hsieh and Shannon (2005)). This research uses direct content analysis as a strategy to code the transcripts of the interviews. The choice of the direct approach is basically because the direct approach is fruitful to validate or extend conceptually a theoretical framework or theory (Hsieh & Shannon, 2005) which is in line with the aim of this dissertation focus on exploring and informing organizations how business users develop insights in an SSBA environment.

After the initial coding using S-D logic core components, a second iteration of coding with a more inductive nature took place within each category of codes. For example, RI is a first-level code that originated from S-D logic. Within the coded text, new codes emerged such as technical resources, support, setup and, engagement.

To manage the coding and analysis process, qualitative data analysis software "QSR NVivo" was used. The main aim of this software is to help and support organizing the empirical material (interview transcripts, observation notes, and other documents) in such a way of enabling fast access, analysis and visualization of data. NVivo was very useful as it supports the creation of a visual mind map based on the theoretical lens adopted and convert it to nodes (see Figure 10).
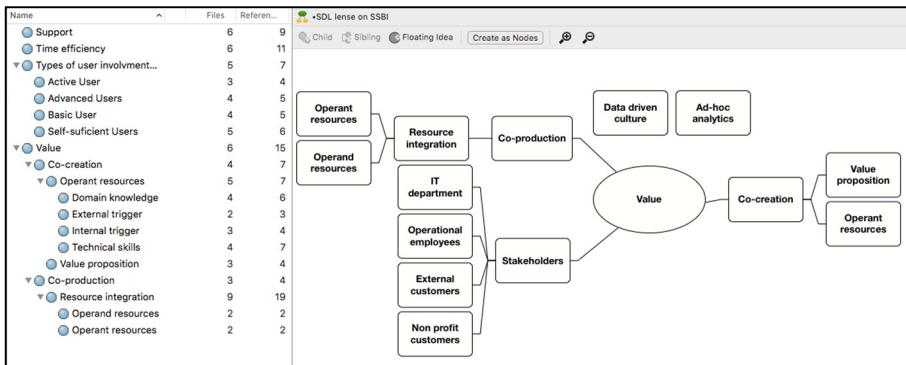
Figure 10:
Example of mind-map and nodes

Second, data display is where they define it as "an organized, compressed assembly of information that allows conclusion drawing and action" Miles et al. (2014, p. 32). In this activity, previously coded text was further analysed, categorized and organized in a more abstract view while maintaining the main findings and relevant information. Through the appended papers, this research has visualized such information using tables, graphs, and models to represent the processed information enabling conclusion drawing and relevant contributions.

Third, conclusion drawing is the interpretation of the findings and the final contribution the data has to present. It starts after the first reading of the interview transcripts where it is possible to notice some patterns and trends within the data however at the beginning of the data analysis it has a fuzzy and uncertain nature and it gets more and more grounded and concrete with further analysis.

To summarize, this research followed Miles et al. (2014) data analysis framework to structure the process. Initial codes were developed upon the S-D logic main concepts presented in Chapter 3. Those codes are more general in nature as they reflect general concepts like co-production, co-creation, resource integration, service exchange, and institutions. The second level of coding followed and was generated incrementally while analysing our data (Miles & Huberman, 1994) while keeping in mind the main concepts. The second iteration was rather inductive, and the codes emerged from the data itself.

4.6 Ethical Considerations

Ethical conduct has increasingly become crucial in the social sciences research method. Researchers found themselves in the dilemma between clear adherence to ethic conduct procedures while complying with regulatory regime requirements from ethic committees. Beauchamp and Childress (2001) defined ethics as a generic term for various ways of understanding and examining the moral life. It is concerned with perspectives on right and proper conduct. Increased research activities have had a great impact on the society, thus there is a potential need to monitor and ensure that ethics are taken seriously and embraced within the research process. The need to incorporate ethics is to enhance quality and produce what is right, good and virtuous as a by-product of research. It is important that research integrity is incorporated to assist in the validation of the research and enforce researchers to behave ethically. There is a great need to avoid and eliminate scientific misconduct or corruption so as to produce more good to the people and hence minimize harm to them. Israel and Hay (2006) argued that researchers need to develop better understandings of the politics and contexts by which ethics are regulated. In this research, I have considered and tried to comply with important ethical issues such as informed consent and confidentiality in order to avoid causing harm.

4.6.1 Informed Consent

It is important that the research participants understand exactly their involvement in the research project and what they have authorized (Seale, 1999). In order to assure ethical conduct, the participant was introduced to the subjects, the purpose of this research, the part of the research that this interview will be used for, and the potential risks that they could face. Also, they were informed that the interview would be recorded for further analysis and interpretation. All the mentioned information revealed to the participant is considered as part of the informed consent, which aims to minimize the possible harm, and risk, and increase the trust of the participants, hence protects participants and the agencies from unpleasant consequences. Furthermore, the participation in our research was completely voluntary and lacked any kind of pressure or influence performed from superior employees or managers. The anonymity of the participants was guaranteed in case they required it. This is due to the lack of direct identifiable information of the

participant. We had also enforced the anonymity by ensuring that the data collected would not be crosschecked with any other source of information that could reveal the identities of the participants.

4.6.2 Confidentiality

In this thesis, confidentiality was considered crucial and necessary procedures were taken to ensure that it was complied. Confidentiality of research participants was protected so that their private data will not be reported, however in case there was a need to reveal their personal identifiable information, there shall be a formal agreement, which gives the approval (Israel & Hay, 2006; Singer & Vinson, 2002). Protection of data collected in a research is an important step in achieving confidentiality. During the interviews, a formal written agreement with the participants was in place in order to enforce the efforts of maintaining the confidentiality of all information collected. In an effort not to disclose the information of the participants, the names and details of participants involved in this research will not be made available to anybody except to the author of the thesis.

4.6.3 Non-Disclosure Agreement

One of the most common ways companies and individuals protect their intellectual property is through what is called a Non-Disclosure Agreement (NDA) (Klee, 2000). Due to the high market competition, the selected organization required us to sign an NDA assuring that no sensitive information that may affect their competitive advantage will be published without their consent. The creation of such a document was complex as there was a need to maintain the trustworthiness of the findings without contaminating it with bias. The initial requirement was that any publication should first get the approval of the organization before being submitted for review. This requirement did not comply with these thesis standards as they had the possibility to reject the findings, which would compromise the trustworthiness of the results. After some negotiation, we agreed that such a condition will only apply for data collected within four months or less of publication due to its sensitivity. This condition did not affect the published papers as the publication came after eight months of the data collection.

4.7 Concluding Remarks

Through an interpretative case study, this dissertation investigates SSBA in a digital marketplace and collects empirical evidence from three main sources: interviews, observation and documents. All data has been transcribed, coded, and analysed using Miles et al. (2014) qualitative data analysis framework managed by a qualitative data analysis software "QSR NVivo" to organize the empirical material. As it will be presented in the next chapter, the empirical data has produced five papers collectively addressing the aim of this dissertation.

5 Research Papers

This chapter provides a summary of the dissertation's appended papers. Each paper is presented together with its publishing outlet and a shorter version in case there is one. This chapter also includes a paper produced (Section 5.5) that is relevant to this dissertation. The presentation of each paper will adhere to the following structure: background, aim, method, findings, and key discussion points

5.1 Paper I:

From an Information Consumer to an In-formation Author: The Role of Self-Service Business Intelligence.

SSBA is a relatively new phenomenon in the industry that promises to enable more agility in data analytics by empowering employees with better access to many resources within their organizations. Resources such as data access, data models, analytical tools and support are provided under the supervision of the IT/BI department. In an SSBA environment, employees assume control of the data analytics process by using their competencies to operate and interact with the environment resources to gain autonomy and independence from the IT/BI department and to become more agile in decision-making and more of an information author than an information consumer.

Even though SSBA is considered a rather new trend in the industry and is promoted by technology vendors like Tableau, Qlik and many others, it still has roots in a well-established research stream in academia named SST. From a technological context, a widely used definition of self-service technology (SST) is: "the technological interface that enables customers to produce a service independent of direct service employee involvement" (Meuter et al., 2000, p. 50, p. 50). Additionally, J. Wang and Namen (2004) define SST as Technology Based Self-Service (TBSS) to denote the activity or benefit built on hard technology that the service provider offers to their customers so they

could perform their service requests fully or partially by themselves. SST emphasis the technology itself whereas TBSS focuses on the activities performed directly or indirectly by the customer to receive a service (J. Wang & Namen, 2004). Interestingly, these two broad definitions target a customer-business relationship, ignoring the instances when SST can be used within an organizational setting. Furthermore, self-service technology is defined based on its application and context such as Internet-based Self-Service Technology (ISST) (Schultze & Orlikowski, 2004).

The point of interface between SST and SSBA is that they both aim at providing some kind of specially designed and customized service to a specific party aiming at granting more independence and control over a specific task. Examples could be either to book a hotel room or book a flight through an online booking system or explore data and develop insights by using tools and technology provided.

Aim:

The aim of this paper is to explore the SSBA environment and investigate the main components that are necessary to expand the role of business users from information consumers to information authors.

Method:

To fulfil the aim, this paper draw parallels between SST and SSBA and performs a systematic literature review on SST published articles in several major journals including the basket of eight journals of IS. By following Vom Brocke et al. (2009) guidelines for crafting a literature review in the IS domain as shown in Figure 11, 81 articles were identified and analysed.
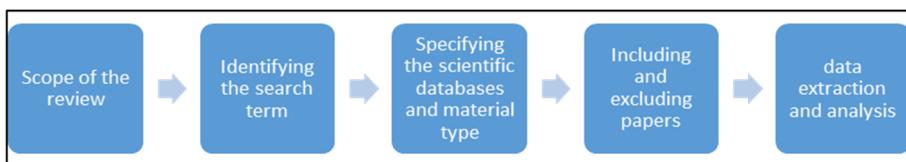
Figure 11:
Literature review process (Vom Brocke et al., 2009)

Findings:

The results show that five major components, namely co-production, autonomy, ease of use, control, and trust play an important role in enabling SST with a special focus on co-production which sometimes is referred to as co-creation.

Key discussion points:

The process of co-producing the service is not trivial. It requires a balance among the analytical tasks at hand, the technological resources available, and the user' competencies. The more these entities are in balance the more effective co-production is. Simple analytical tasks may require basic technical and analytical skills to access data from one or two data sources; however, more advanced tasks require advanced technical skills to work with many data sources. From an SSBA perspective, business users have a higher responsibility. Shifting from information consumers to information authors implies also that responsibilities are shifting from the IT/BI departments to other organizational departments.

Reference:

Bani-Hani, I., Tona, O., & Carlsson, S. (2018). From an information consumer to an information author: a new approach to business intelligence. Journal of Organizational Computing and Electronic Commerce, 28(2), 157-171.

- A shorter version was presented at the American Conference on Information Systems (AMCIS) 2017. " Bani Hani, I., Tona, O., & Carlsson, S. A. (2017). From an Information Consumer to an In-formation Author: the Role of Self-Service Business Intelligence. American Conference on Information Systems (AMCIS) 2017."

5.2 Paper II:

A holistic view of value generation process in a SSBI environment: a service dominant logic perspective.

Background:

The nature of today's business demands that business intelligence (BI) extends to an operational level to support a variety of employees during their tasks (Böhringer, Gluchowski, Kurze, & Schieder, 2010) and to minimise the risk of

no fact-based decisions (Abelló et al., 2013). Often, BI specialists and/or other power users at functional departments are overloaded (Kobielus, Karel, Evelson, & Coit, 2009) by constant requests of reports from different organisational levels (Yu, Lapouchnian, & Deng, 2013). Self-Service Business Intelligence (SSBI) – as a new trend attracting industrial attention – promises to enable executives, managers, analysts, and knowledge workers to not only access data but also to be able to design and build reports based on their respective needs (Abelló et al., 2013). In this way, an end-user becomes a data producer in addition to the current data consumer profile. However, setting up an SSBI is not trivial and includes many touchpoints between an IT/BI department and business people, such as during the selection of data sources and specifications of a data field, data model, and semantic layer (Imhoff & White, 2011). In general, the operational level in an organisation encompasses a wide range of employees (such as sales, marketing, operations, and customer care). An ineffective design of SSBI environment (Imhoff & White, 2011) increase the chance of wrong or uneducated self-service step during data selection and analyses which in turn might affect the quality of a business decision.

Aim:

Even though there is research done on SSBI, there is little empirical knowledge about the process of building a SSBI service or setting up an SSBI environment and the role of the user in this process. The aim of this paper is to describe how an SSBI environment is enabled through the involvement of different stakeholders and their respective roles.

Method:

Drawing on S-D logic as an analytical framework, this study uses an exploratory single case study of a major Norwegian online marketplace to investigate how the organizations' stockholders collectively enable an SSBI service in their environment and provide the required optimized resources to its employees to achieve independence in data analytics.

Findings:

The findings identify two major phases: co-production and co-creation. In co-production, several different resources are exchanged among actors to populate the SSBA environment with data models and business logic (see *Figure 12*). The data models should be comprehensible by operational users in the organization as key users and beneficiaries of the service.
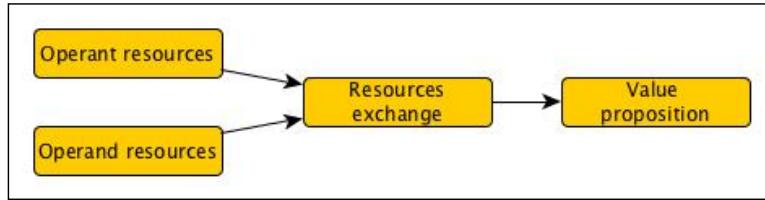
Figure 12:
Co-production process

However, in co-creation, users engage with the resources in the SSBA environment and use data models provided from the first phase (co-production). Through this usage, the proposed value is transformed into value in use (see Figure 13) where users can feel the actionable benefits that this specific self-service environment provides (Vargo & Lusch, 2004, 2008). The actual usage of the platform requires the integration of resources from the user (operant) (such as business knowledge, technical skills, and time) with resources imbedded in the self-service platform such as easy-to-use data models, data source access, and export functionalities.
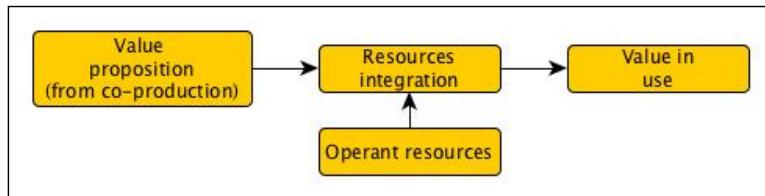
Figure 13:
Co-creation process

Both phases are crucial to SSBA as the co-production phase serves as an input to the co-creation phase which generally defines the actual engagement of the user in data analytics to achieve independence.

Key discussion points:

These findings support the fundamental notion that co-production is an important step in co-creation of value and that the healthy interaction between both phases (co-production and co-creation) enables a healthy co-creation of value. This is reasonable, as the involvement of business users at the early stages of co-production will increase the chances of a beneficial proposed value. Given the service nature of an SSBA environment to provide actionable

and operational information needed during daily work, users should be involved during the design and implementation of data models. This study shows that operant resources are present during the phases of co-production and co-creation. From a firm-customer perspective, the operant resources could be the business employees (the firm resource) or the customer (service beneficiary).

This study indicates several implications for organizations. First, companies should invest in a collaborative environment where business users and IT staff/business analysts/ data scientists may come together during the co-production phase. Second, companies should invest in the necessary trainings that business users might need to be capable of working with analytical tools and reporting applications in an SSBI environment. Third, companies should assess the value proposed after co-production as whether it is aligned with the company's objectives or more work needs to be done.

Table 13:
Summary of the findings

	Co-production		Co-creation	
	Resource Exchange	Value proposition	Resource Integration	Value in use
Technical department	Analytical skills, technical skills	Free-up time for IT personnel, centralized data access to users, less ad-hoc requests	Technical knowledge, support, analytics validation, data model update	Focus on advanced analytical tasks, self-efficiency of routine requests, prevent abusing the data warehouse
Business users	Business knowledge, business experience	Autonomy, freedom for exploration, responsiveness, data access	Business knowledge, time, technical skills (low-high), analytical skills, motivation, understanding the firm business model	Data source connection, analytics creation, Effectiveness in customer response, efficiency in task performance, personal gain
SSBA Environment	Ability to connect to different data sources, data loading and consistency	Platform for insight discovery	Integrated data model, standard dashboards, data source access, data export, insight sharing	Data model improvement, increase adoption

The study provides a rich description of the building process of an SSBA service and the roles of several stakeholders involved as well as the major elements that are involved in each phase. This paper describes how an SSBA service is built through the essential collaboration between the IT/BI staff and the business users involved. SSBA co-production is an important step in

enabling a healthy co-creation and cannot be underestimated. Based on this research study and empirical accounts, this paper develops an empirically grounded understanding and description of the role of co-production and co-creation in building SSBA service.

Reference:

Bani-Hani, I., Pareigis, J., Tona, O., & Carlsson, S. (2018). A holistic view of value generation process in an SSBI environment: a service dominant logic perspective. Journal of Decision Systems, 1-10.

- An earlier version was presented at the 19th Open Conference of the IFIP WG 8.3 on Decision Support Systems (IFIP DSS 2018). "Bani-Hani, I., Pareigis, J., Tona, O., & Carlsson, S. (2018). A holistic view of the value generation process in an SSBI environment: a service dominant logic perspective. Paper presented at Open Conference on Decision Support Systems (IFIP WG 8.3) 2018."

5.3 Paper III:

Modes of engagement in SSBA: A service dominant logic perspective.

Background:

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 on an SSBA environment to empower business employees and decentralize the analytics capabilities. Yet, little is known about how SSBA facilitates business employees' independence, and moreover, the value that is co-created.

Aim:

Little is known about how effectively SSBA is facilitating business users' independence, considering that a possible 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 analyse data? Indeed, these questions focus 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 about its enablers. To fulfil 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.

Method:

Through a qualitative approach, this study uses two sources of evidence: thirteen face-to-face 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. The interview guide was developed based on S-D logic main components and questions in relation to resource integration in SSBA and the service exchange nature and institutions within the organization. By doing so, three main themes were created that provided a focused investigation of the phenomenon with an S-D logic 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.

Findings:

Based on empirical data from a major Norwegian online marketplace and drawing on S-D logic as an analytical framework, this paper identifies three main modes of data engagement in SSBA: no dependency, high dependency, and low dependency. Furthermore, this paper identifies the required business users' resources in the analytical processes in each mode (see Table 14).

Table 14:
Business users capabilities required in SSBA

Process	Capabilities needed
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)

The findings of this paper highlight three main modes of engagement the user exhibits while integrating resources to ultimately generate the desired insights namely (A) No Dependency Mode (NDM), (B) Low Dependency Mode (LDM) and (C) High Dependency Mode (HDM) (see Figure 14). This categorization is based on the premise that the SSBA process is not trivial and sometimes the users need support, especially from techno-oriented employees. The support is therefore provided to compensate for the lack of the technical knowledge needed to accomplish a task and generate insight into data.

Key discussion points:

A major goal of SSBA is to enable more user independence in generating insights. In an SSBA environment, insights are generated mainly through three modes of engagements: No Dependency Mode (NDM), Low Dependency Mode (LDM), and High Dependency Mode (HDM). In NDM (Mode A), business employees are involved independently in gathering data from different sources, data preparation, data analysis, building visual representations of the processed data, and interpreting the results to generate

insights without the support of techno-oriented users. In LDM (Mode B), business employees are involved independently in data analysis, building visual representations of the processed data, and interpreting the results to generate insights with the partial support of techno-oriented users. In HDM (Mode C), 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.
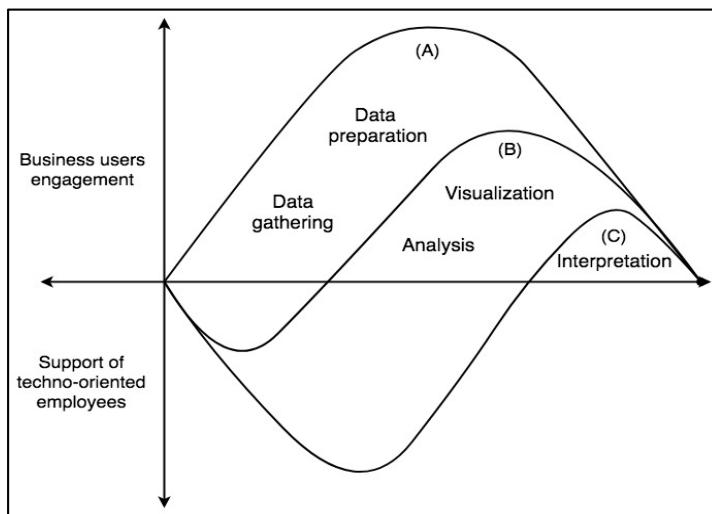
Figure 14:
Engagement modes in SSBA

This paper suggests that business employees will integrate mainly intangible resources utilising 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, the investigated case highlights three main scenarios of engagement. To conclude, SSBA, a new approach to BA, aims to empower business employees by making data analytics independently available to them. The 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 characterized by three modes, which show three ways business employees integrate resources with techno-oriented employees. From an independence perspective, this paper evaluates the three modes and identifies the 'best case scenario'. Departing from that, it discusses 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, this paper presents some practical implications and recommendations for organizations on how to encourage their business employees to become independent during analytical tasks.

Reference:

Bani-Hani, I., Tona, O., & Carlsson, S. (2019). Modes of engagement in SSBA: A service dominant logic perspective. In 25th Americas Conference on Information Systems, AMCIS 2019. Association for Information Systems.

5.4 Paper IV:

Patterns of Resource Integration in the Self-Service Approach to Business Analytics.

Background:

In a typical SSBA environment, the technical department provides data, tools, and technologies specifically optimized to lower the operational complexity of processing data into information. As a result, the employees become more autonomous in fulfilling their own information needs, which in turn enables the technical department to focus more on strategic tasks (Alpar & Schulz, 2016; Bani Hani, Deniz, et al., 2017; Corral, Schuff, Schymik, & St Louis, 2015). In such a scenario, the value of SSBA is co-created between the different actors (which is, in this case, the business and technical employees). Co-creation occurs mainly as a result of the integration of the employees' competencies (such as knowledge, experience and technical capabilities) with the previously mentioned environment resources, that are enabled and maintained by the technical department. As such, resource integration is considered a central activity in an SSBA environment and causes value generation or, in other words, it processes data to generate business insights. Therefore, it is important to have a sound understanding of how resource integration occurs in an SSBA environment and more specifically, to describe

the resource integration patterns and contributes to a successful value generation given the resources available.

Aim:

The aim of this paper is to investigate how resource integration occurs in an SSBA environment.

Method:

This paper adopts a single case study design (Hayes, Barlow, & Nelson-Gray, 1999). Through qualitative interviews including field visits and secondary data in the form of documents, we provide rich descriptions (Schultze & Avital, 2011) and insights to investigate how resource integration occurs when business users interact 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 requirements: (a) a data-intensive organization and (b) an enabled SSBA environment for its employees.

There are two sources of evidence in this study: semi-structured interviews including field visits and both organizational documents with detailed employee surveys and also internal documents such as data sources, tools and techniques for data analysis. Thirteen semi-structured interviews (15 hours were recorded, transcribed, and loaded into NVIVO11 with the consent of the participants) took place at Finn.no between February and May 2016, in Oslo, Norway.

Findings:

Based on the empirical data of a major Norwegian online marketplace and drawing on S-D logic as an analytical framework, this paper first identifies the different types of actors involved in an SSBA environment. Second, it discusses the main types of institutions enabling and controlling resource integration in an SSBA environment, and finally it introduces and describes the resource integration patterns occurring in an SSBA environment.

Key discussion points:

As previously mentioned, SSBA is an approach to data analytics that basically empowers its users with the ability to experience a certain level of independence while exploring and exploiting data in the process of addressing a business need (Bani Hani, Deniz, et al., 2017; Bani-Hani, Tona, et al., 2018). However, this process is not as simple as it seems and having the appropriate

configuration of institutions, resources and actors in the SSBA environment is an important key to its success.

The main actors involved during an analytical task, in an SSBA environment, are Business Users (BU, who engage in daily analytical tasks including business support) and the Techno-Oriented Employees (TOE, who support business employees). Most of the TOE belong to the IT/BI department and other more specialized technical groups, whereas BU work in other departments, such as product development, sales, marketing, and public relations.

Based on SDL literature and in line with our findings, three types of institutions enable and control user behaviour in an SSBA environment (see Table 15). Regulative institutions such as regulations and observation affect the business user behaviour, that is driven by mainly self-interest to avoid any potential sanctioning resulting from ill-informed decisions. This type of institution pushes the business user to engage with data and to back up those decisions by facts. Normative institutions are basically the norms and rules that are influenced by the organization's vision, strategy, and strategic plane. For example: the need to be more independent, self-reliant and data-driven in decision-making as a new organization strategy. Cognitive institutions, as described by Scott (2013), represent the deepest connection between the actor and the field, and are mainly the institutions related to the actors' perception of the SSBA environment, its benefit, potential and value.

Table 15:
Institutions in an SSBA environment

Institution type	Leads to:	In SSBA context
Regulative	behaviour driven by self-interest	Nurtured by the need to be well informed in decision-making and avoid any negative consequences of an ill informed decision.
Normative	behaviour driven by social restraints	Nurtured by the organizational strategic vision, plan and socially constructed routines.
Cognitive	behaviour as 'taken-for-granted'	Nurtured by the presence of technology, tools and resources present in the SSBA environment.

While institutions describe user behaviour in an SSBA environment, resource integration depicts the actual engagement of an actor with the resources available by enacting and interacting with data, technology, other actors and resources in order to address a particular business need. Based on our findings, two types of resource integration occur, direct resource integration and clustered resources integration.

In the direct resource integration, the enactment of resources occurs in a linear fashion. A business employee enacts Personal Competencies (PC) to interact with Resources R1, R2 … Rn until data insight is generated. There are no specific rules on what and when certain resources are enacted because it mainly depends on an employee's PC and how institutions affect his/her behaviour.

In the clustered resource integration, due to the fact that the actor's PC consists of technical skills, experience, and business knowledge, the probability of requiring assistance in certain tasks cannot be neglected. In such case, the enactment of resources does not follow a linear fashion but rather a nested one. For example, a business employee enacts PC to interact with R1 then R2, subsequently may be followed by Others Persons Competencies OPC1, and then OPC2 … OPCn, Rn. There is no specific path wherein R or OPC comes first, however, every time an OPC is enacted a cluster is created. The reason for the emergence of such a cluster is that each OPC represents the competencies of other employees in an SSBA environment or what we refer to as support actors. Those actors in their turn can enact ER to provide assistance, hence creating a cluster.

The 1st tier cluster constitutes the direct support that a business user provides in case the initial actor lacks specific business understanding or the techno-oriented user answers a technical question. The 2nd tier cluster emerges when the 1st tier cluster could not provide the needed support, and where more specialized people are needed. Both scenarios are the empirical proof of the network nature of resource integration described in the process of value co-creation described by SDL (Overkamp et al., 2018; Vargo & Lusch, 2016a).

Reference:

Bani-Hani, I., Tona, O., & Carlsson, S. (2020). Patterns of Resource Integration in the Self-Service Approach to Business Analytics. *In Hawaii International Conference on System Sciences.* (HICSS).

5.5 Paper V:

Enabling organizational agility through self-service business intelligence.

Background:

Organizational agility is the capability of a company to address challenges that can occur from inner or outer environments for the sake of moving with more flexibility and speed compared to its competitors (Sambamurthy et al., 2003; Singh, Sharma, Hill, & Schnackenberg, 2013). Rather than being ad hoc and unsystematic, organizational agility is conceptualized as systematic variations in organizational outputs, structures, processes, and actions that are executed consciously to gain a competitive advantage (Sanchez, 1995; Tallon & Pinsonneault, 2011).

Many products and services are embedded with digital technologies in which they can operate as digital platforms to enable new forms of business models (Bharadwaj, El Sawy, Pavlou, & Venkatraman, 2013). One of these business models is a multi-sided platform where many different stakeholders are brought together via their interactions through the a digital platform to conduct commercial activity, i.e. a digital marketplace (Evans & Schmalensee, 2016). In this context, the main concern of the platform owner is to figure out how to implement various incentives in the marketplace so that participants can interact with each other given that the value creation is contingent upon this (Anderson Jr, Parker, & Tan, 2013). Furthermore, digital marketplaces are usually "situated within the broader ecosystems of firms, governments, regulation, and other institutions" (Evans & Schmalensee, 2016) in which the owner of the digital marketplace needs to comply with laws and regulations coming from these bodies and reflect those changes in its platform when needed.

Moreover, in an era where competitive advantage is fleeting (D'Aveni, Dagnino, & Smith, 2010), any given organization needs to move faster relative to its competitors and have the capacity to be flexible to effectively change and adapt to new purposes and respond to emerging possibilities (Agarwal & Tiwana, 2015), therefore having the capability of organizational agility (Lu & Ramamurthy, 2011). Such a capability can show two different dimensions: market capitalizing agility and operational adjustment agility (Lu & Ramamurthy, 2011). Market capitalizing agility refers to a firm's ability to constantly look for areas to improve upon in their offered product or service and leverage on these to meet ever-changing customer needs. Operational

adjustment agility, on the other hand, refers to a firm's ability to address their inner workings – distributed responsibility, data ownership and transparency across organizational units, etc. – as a foundation for responding to outer changes.

In order to achieve such firm-wide capability, organizations need to create leverage through the processing of large volumes and distribute up-to-date information with the help of various IT-enabled systems (Volberda, 1997).

Aim:

In this paper, we study the role of self-service business analytics (SSBA) in enabling organizational agility. In particular, the research question addressed is as follows: How does SSBA enable organizational agility in a multi-sided platform? Two types of organizational agility were the focus of this paper – namely, market capitalizing agility and operational adjustment agility – and identify how SSBA enables these capabilities in a multi-sided platform environment.

Method:

The research method adopted in the paper is the qualitative interview, as we believe that the interview technique will provide rich descriptions and insights into understanding the role that SSBA plays in the organizational process and business. To do so, it was important to have a good understanding of how SSBI is used in different departments of an organization in terms of its role, usage and business process facilitation, which we believe is aligned with the strength of qualitative studies.

Findings:

Through 12 qualitative interviews that focused on Norway's biggest digital marketplace, the results indicate that SSBA plays an important role in enabling (1) market capitalizing agility by providing a better understanding of supply and demand participants, more access to traffic data and user clickstreams, fast response to requests, and increased access to supply and demand navigation behaviour and (2) operational adjustment agility by redefining current organizational structures, empowering employees, providing equal access to organizational level data, and opportunities for data manipulation. The findings provide empirical evidence for the role SSBA plays in enabling organizational agility within the context of a multi-sided platform environment.

Key discussion points:

There is a critical call on organizations to show agile capabilities – move faster relative to their competitors, adapt to changing requirements, and to respond quickly to emerging opportunities (Agarwal & Tiwana, 2015). Agility is mainly achieved through two main dimensions: market capitalizing agility and operational adjustment agility.

On enabling market capitalizing agility, SSBI enables different organizational units to understand supply and demand needs based on their special interests, and therefore targets each stakeholder individually. In addition, since SSBI provides different organizational units with the ability to target various stakeholders, it raises the responsiveness of the platform owner to its environment. However, though the usage of SSBI decreases the interdependency between organizational units on their work processes, it does not eliminate that interdependency. It is also important for any employee to learn how to use and engage with SSBI so that he/she can leverage the opportunities provided by the SSBI system. Moreover, SSBI enables access to aggregate level platform data to keep the digital platform and its underlying infrastructure updated. Rather than focusing on the stakeholders' individual needs, SSBI helps in leveraging an individual stakeholder's footprint on the platform to further improve it. Finally, SSBI is an important instrument in matching the demand and supply sides of a multi-sided platform because it can provide detailed information about the interaction patterns of stakeholders on the digital platform and helps to leverage that information to better design matching mechanisms (Van Alstyne, Parker, & Choudary, 2016).

On the other hand, on enabling operational adjustment agility, SSBI changes the interdependency levels of organizational units among each other when conducting their individual work, which increases the flexibility among organization units and response time to requests and therefore appears to be a sign of more agility in organizational structures (Tallon & Pinsonneault, 2011). In addition, SSBI empowers employees to make sense of data and therefore promote the data-driven culture (Watson, 2009). Furthermore, the empowerment of organizational users is enabled because SSBI increases access to organizational level data and the possibility of creating various data mashup based on different requirements. In Table 16 below we summarize our findings in relation to the discussion and present how SSBI enables organizational agility.

Table 16:
SSBA enabling organizational agility

Organizational Agility	SSBI enablement	
	What it enables	How it enables
Market capitalizing agility	Better understanding of supply and demand.	Through the diffusion of supply and demand needs to specialized units
	Fast response to requests	Through making each organizational unit capable of responding to user requests without any external reliance (IT/BI).
	More access and freedom to supply and demand navigation behaviour	By the exploration and exploitation of supply and demand data generated though the multi-sided platform (macro level)
	More access and freedom to traffic data and user clickstreams	By the exploration and exploitation of supply and demand data (micro level)
Operational adjustment agility	Nature of relation with the core unit	Through the independence of IT/BI department
	Empowerment	By the ability to create ad-hoc reports and analytics.
	Data access and usage	Through the ability to perform data mashup and exploitation/exploration data.

Reference:

Bani Hani, I., Deniz, S., & Carlsson, S. (2017). Enabling organizational agility through self-service business intelligence: The case of a digital marketplace. In Pacific Asia Conference on Information System (PACIS) (p. 148).

6 Answering the Research Questions

In this chapter, the research questions are discussed based on the findings from the appended papers. The aim of this dissertation consists of two major parts, first, the *SSBA environment*, which organizations enable to support idea of user independence in business analytics and second, *resource integration,* where users engage with the SSBA environment resources to generate insights.

To fulfil the aim, this dissertation first addresses *RQ1"How do organizations enable an SSBA environment?"* in Section 6.1 by discussing the nature of the SSBA environment based on the findings from appended Papers 1 & 2. Then in Section 6.2, RQ2 "*How users integrate resources available to generate insight from data?*" is answered based on the findings of Papers 3 & 4 focusing on the user engagement in an SSBA environment and resource integration (see Figure 15). Even though this dissertation defines the organization as the level of analysis, however, it starts with the organization then moves towards a more specific and user-centric level to better understand SSBA at a more granular level especially the user engagement with resources. This shift is evident in the two sub-questions above and necessary to better describe and explain the SSBA environment that the organization provides to its users and how the users, in turn, engage in such an environment to generate insights.
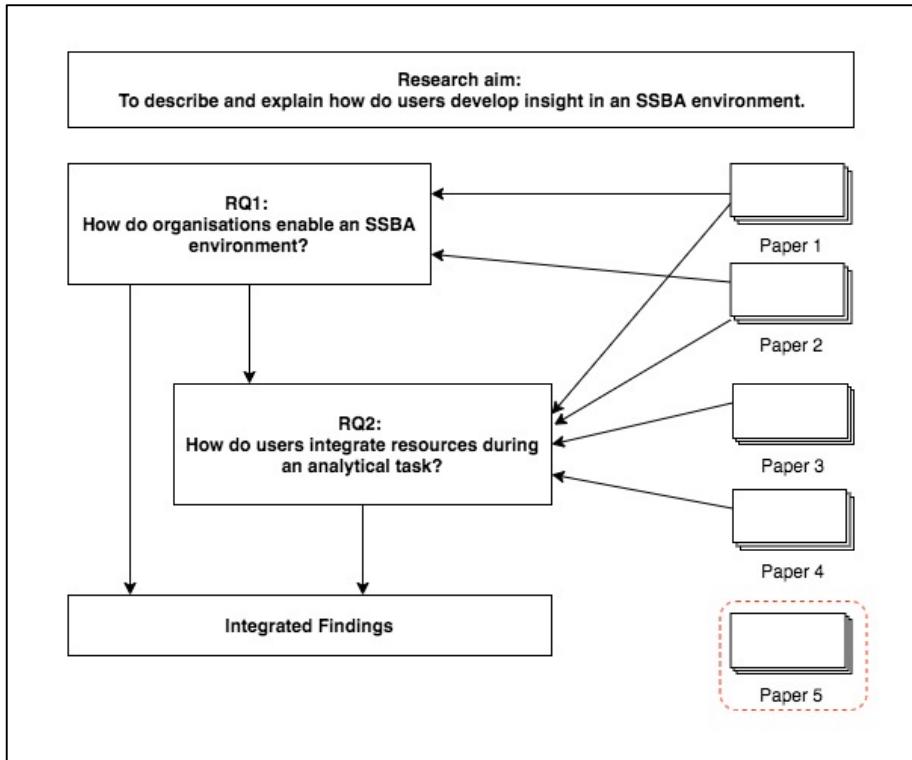
Figure 15:
Paper contribution to research question and aim.

6.1 How Do Organizations Enable an SSBA Environment?

Studies in the SST literature stream tend to focus on a single or specific product such as Internet banking, booking systems, ATM machines, etc. (Curran & Meuter, 2005; Dabholkar, 1996; Dabholkar & Bagozzi, 2002; Dibb et al., 2013; López-Bonilla & López-Bonilla, 2013; Meuter et al., 2000; Scherer et al., 2015). In contrast, SSBA (considered as a type of decision support system) entails the use of many tools and applications in an organization's environment provided specifically to assist employees in their decision making. Many authors have defined SSBA from different perspectives (Imhoff & White, 2011; Pal, 2016; Schuff et al., 2016; M. Weber, 2013), leading to an unclear

conceptualization of the SSBA nature, what it represents and what the basic elements or factors are that enable such an SSBA environment. This dissertation defines SSBA as an approach to data analytics supported by an environment that lowers the business user's dependency on technical users while generating insight into data.

The main promise of SSBA is to decrease the users' dependency on technical employees and promote autonomy in data analytics to generate insights (Imhoff & White, 2011; Pal, 2016; Schuff et al., 2016; M. Weber, 2013). To this end, users are free to access data (provided by the technical department) and perform analysis using the tools and technologies available. This forms a dyadic relationship between the SSBA user and the technical department where the technical department provides support and maintains the SSBA environment wherein the user takes ownership of their data analysis tasks. The dyadic relationship results in a shift of responsibilities from the IT department to the SSBA business users leading to a change in the role of the user. The user becomes more of an information author rather than a consumer as shown in Paper 1.

The answer to RQ1 is mainly found in P1 and P2. In P1, this dissertation investigates the nature of SSBA and performs a systematic literature review to uncover what enables an SSBA environment. P1 highlights five main elements that collectively contribute to enabling an SSBA environment within an organization (see Table 17).

Table 17:
Elements enabling SSBA environment

Factor	Nature	Meaning	Description
Control	User perception	Having control over the insight generation process can influence both the intention to engage in data analytics as well as satisfaction.	From a psychological perspective, control boosts the self-efficacy of the user, which is strongly connected to the personal capabilities (such as, computer and technology literacy). Self-efficacy highly influences the acceptance, usage intention, and perceived value of SSBA. Once users have control over insight generation in an SSBA environment, they start producing the service they need independently hence fulfilling the promise of SSBA.
Trust		An SSBA environment should also provide a feeling of trust for its users concerning the relevance of provided data and insight generated	Trust can be described as a two-dimensional construct: 1) trust believe - the user perception of the SSBA environment in terms of benefit, reliability, value embedded and 2) trust intention - the willingness of the user to expose himself to the possibility of loss. In other words, users in SSBA environment should trust the data provided and be comfortable in presenting insights they found.
Autonomy		Users should rely on themselves by feeling free to engage with data anytime they deem it necessary without going through the bureaucracy of requesting the reports from an IT/BI department.	Users explore and exploit available data sources to perform data analyses and use it to answer questions. In a conventional BI environment, employees forward ad-hoc requests to the IT/BI department. A considerable time lag can occur until they receive a response, depending on the overload of the IT/BI department, thus making them completely dependent and reliant. On the opposite, in SSBA environment enables a self-service approach to data analytics, which weakens the link to IT/BI departments, if not making it absent. In SSBA environment, users have the needed resources to act independently in accomplishing a data analytical task unless they need advanced expertise.
Co-production / Co-creation	Activity or process	The actual engagement of users with many resources available throughout the process of solving an analytical task.	An important component of the self-service environment, as seen in our findings, is the Co-production (where the user is involved in the environment setup), and Co-creation (where the user use the environment resources). In an SSBA environment, resources are used in coherence with user's technical and intellectual skills controlled by institutions to access data, structure data, formulate ideas, generate information and gain insights about a specific task.
Ease-of-use	Technology characteristic	Pleasant, easy to use technological tools, which requires minimal skills to operate.	The main goal behind SSBA is enabling employees to serve themselves during task accomplishment without the need for assistance. To do this, research highlights the importance of this factor as it aims at lowering the technology operational complexity required to generate insights. Ease of use affects the engagement in an SSBA environment since it requires a user to use personal skills and knowledge in order to operate the tools provided.

To enable a SSBA environment, trust, control, and technology ease-of-use are factors that need to be present and perceived by the users in order to co-produce and co-create. Co-production/co-creation per se is more of an activity rather than a factor. This activity entails an interaction between different parties for a shared benefit and a common goal (Peters, 2016). *Figure 16* represents a model of the basic elements and their relationship in achieving autonomy in an SSBA environment. To better understand this model, let's try to think about it in backwards terms. That is, to achieve autonomy (independence in data analytics), a user should engage with the resources available in the environment and start the process of co-production and co-creation. However, co-production and co-creation is only achieved if the user trusts the resources, assumes control over what resources are needed, and how/when to use them through an easy-to-use technology.

From an S-D logic perspective, value co-creation only occurs when the actors engage in resource integration and service exchange that are controlled and enabled by institutions within a self-adjusting and self-contained ecosystem. Trust and control over data analytics highly affect the actor institutions in terms of the perceived value of the actor engagement with the environment resources and willingness to carry on a task independently and achieve SSBA's main goal.
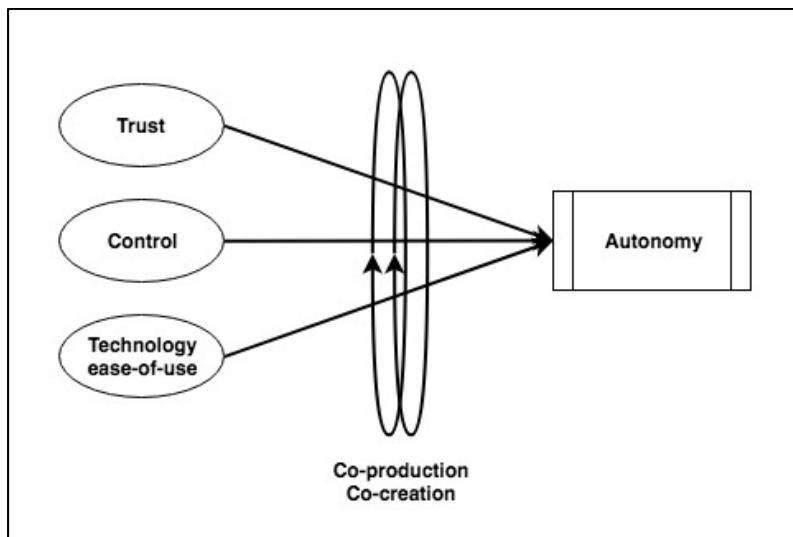
Figure 16:
Basic elements of an SSBA environment drawing from SST

In P2, this thesis further explores the concepts of co-production and co-creation identified in P1 by investigating the processes, differences, and relations towards value generation. Co-production in SSBA is considered an integral and significantly important part of enabling an SSBA environment because it affects the quality of the service provided (data and tools), hence creating user engagement. To enable such an environment, different employees (technical and business-oriented) collaborate together in *exchanging resources* such as knowledge, experience, and skills to identify the best-optimized setup and structure in terms of data and technology, thereby maximizing the proposed service to the users and serving as an input to the co-creation phase. Through a process called resource integration in the co-creation phase, as depicted in S-D logic, users interact with resources such as cleaned data, integrated and understandable data models and tools by using their personal skills, knowledge, and experience to generate the desired outcome. The result of this process is a realized value in the form of insights for making a decision in solving a problem or addressing an opportunity. Both phases are dependent on each other. Co-creation depends on the output of co-production such as optimized data models, technological tools for data analytics, access to clean and relevant data sources and too many more to mention to provide an environment that supports SSBA. In its turn, the co-production phase depends on the feedback from the co-creation phase to sustain such an environment and maintain the optimized resources provided (see Figure 17) which highlights the self-adjusting property of the SSBA environment.
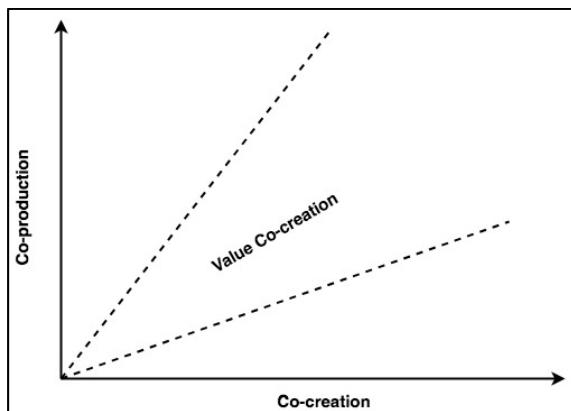
Figure 17:
Relation between co-production and co-creation (from paper 2)

To summarize, the SSBA environment is an environment that supports the notion of user independence in data analytics and provides control over the process of insight generation, which is the main promise of SSBA. It follows that the IT department becomes more of an enabler and less of a controller supporting users in insight generation. To enable an SSBA environment, the IT department needs to closely collaborate with the business users and provide them access to *relevant* data and technologies in line with the competencies (such as technical skills and experience) the users possess, which can be challenging due to the variety of the user's competencies. In contrast, users must have the readiness to be self-reliant and independent in insight generation. To enable an SSBA environment, the organization must realize that providing technology and data access to users is not enough. Based on the findings, they must consider three important pillars. First, they should perceive that the SSBA environment as a service environment wherein the value of SSBA's insights into data is basically co-created and not individually generated. Second, the inclusion of business users in the early stages of building the SSBA environment is crucial for aligning the analytical needs of business users and the resources provided in the SSBA environment. Third, independence is only achieved by empowering business users through three major factors: trust in data, control over the process of data analytics, and the availability of easy-to-use technical resources.

6.2 How Do Users Integrate Resources During an Analytical Task?

As pointed out earlier, the SSBA environment is characterized by the presence of different types of resources such as access to relevant data, technology and tools, support and even organizational institutions which specifically enable the self-service approach in business analytics. Users in such an environment engage with different resources to serve themselves and gain independence from the IT/BI department and more personal control over the process of data analytics. The second research question (RQ2) aims at describing and explaining user engagement in an SSBA environment from a resource integration perspective. Such user engagement is described in P3 by exploring the different modes of engagement present in the SSBA environment with regard to the process of data analytics.

Inspired by the BA architecture (Chaudhuri et al., 2011), data becomes information by going through several steps (see Figure 18). First, BA has to connect to a variety of internal and external sources such as ERP, CRM, SCM, and other legacy systems to gather the needed data (Gibson & Arnott, 2005). Next, starts the data preparation stage in which data is extracted, transformed, and loaded through an ETL process (Gibson & Arnott, 2005) and stored in data warehouses, data marts (March & Hevner, 2007; Watson, 2009), or recently to Hadoop clusters (Phillips-Wren & Hoskisson, 2015). When the preparation stage is complete, data is further analysed and visualized so that users via different devices such as a PC, laptop or mobile device can interpret it into useful information to derive the knowledge necessary for decision-making and action-taking (see Figure 18).

| Data Gathering | Data Preperation | Data Analysis | Data Visualization | Data Interpretation |
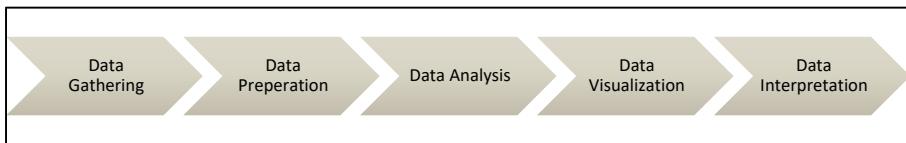
Figure 18:
Data analytics process (based on BA architecture (Chaudhuri et al., 2011))

Based on the data analytics process shown in *Figure 18*, three modes of engagement in SSBA were identified in P3: 'No Dependency Mode', 'Low Dependency Mode' and 'High Dependency Mode' (see Figure 19).

In No Dependency Mode (NDM), business employees solve an analytical task fully independently from techno-oriented employees as shown in *Figure 19*, where the light brown colour signifies the engagement in all steps of the data analysis process. Through an independent scenario, an employee's work efficiency and effectiveness 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 & Siegel, 2014) can be achieved because there will be more autonomous users and fact-based decisions may be infused across all levels of an organization (Davenport, Harris, & Morison, 2010). Furthermore, by curtailing the time needed for techno-oriented staff to handle daily ad hoc data analytical requests, this scenario is supported by recent research which indicates that IT/BI resources should be used more efficiently and effectively on strategic projects (H.-M. Chen et al., 2017; Peppard & Ward, 2016). In such a mode of

engagement, the dominant assumption is that the business user is expected to gather data, prepare data, analyse 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 Low Dependency Mode (LDM) signifies a low dependent business employee as shown in Figure 19 where the light brown colour signifies the engagement in the last three steps of the data analysis process and the dark brown colour signifies the support given to the technical people. Even though business employees possess technical, analytical, and data visualization skills involved in data analyses and data visualization, the lack of other special competencies to engage in other processes, especially data gathering and preparation, hinders them to successfully complete an already-initiated analytical task. Sometimes, 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 their final results. Based on this finding, organizations striving for NDM should support employees during resource integration mainly to increase their self-confidence, trust in data, and to develop the competencies needed to engage in data gathering and preparation. First, through training, employees can obtain a more solid knowledge of the data sources, data preparation, and data quality. And second, organizations can create 'mentorship' programs wherein small groups of business users can work for a specific time with techno-oriented users.

The High Dependency Mode (HDM) represents the most unwanted scenario for an organization that has invested in an SSBA environment mainly because of the full involvement of techno-oriented employees, which is similar to the traditional approach to BA. As shown in Figure 19, the light brown colour signifies the engagement in only the last steps of the data analysis process and the dark brown colour signifies the support given technical people which dominate the total process. In this scenario, business employees possess a very modest technical knowledge permitting them only to navigate through ready-made analytics and interpret information. Such employees are fully dependent on the techno-oriented users in the first four steps of the data analytics process.

NDM

| Data Gathering | Data Preperation | Data Analysis | Data Visualization | Data Interpretation |

LDM

| Data Gathering | Data Preperation | Data Analysis | Data Visualization | Data Interpretation |

HDM

| Data Gathering | Data Preperation | Data Analysis | Data Visualization | Data Interpretation |
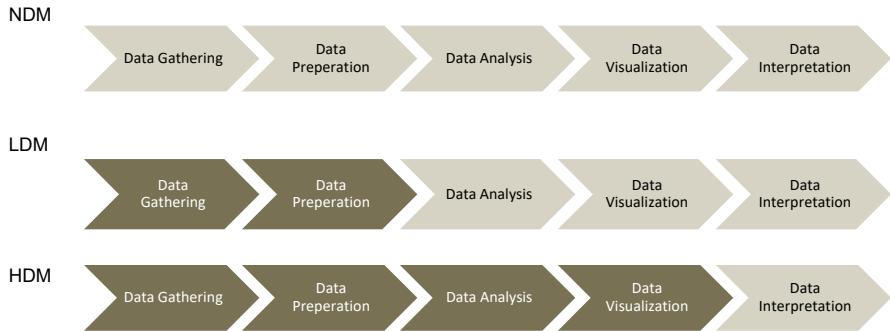
Figure 19:
Modes of Engagement in Relation to Data Analytics Process

For an organization to progress towards scenario LDM and ideally NDM, a data-driven culture (in terms of data analytics) should be promoted, thus particular attention should be directed to institutions and institutional arrangements (Vargo & Lusch, 2016a) such as a having a data-driven mindset. 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 own competencies and developing attitudes, norms, and rules in line with the data-driven mindset. It is worth mentioning that adapting certain work processes to accommodate business employees within this group can also help in shifting to LDM and NDM. By work process, I mean practices which pre-define who gets support in analytical tasks and setting priorities. There should be a 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 NDM. Each of the engagement modes that entail the analytical process and its corresponding resources that business users should integrate during an engagement with data. Having said that, the processes and consequently the required resources of the three scenarios are additive, which means that to move from HDM to NDM, business users should have all resources associated with NDM.

P4 extends the idea of having different modes of engagement in an SSBA environment by describing how the engagement actually happens. Within each mode of engagement, resource integration occurs when an actor enacts SSBA environment resources (including collaborating with other actors) in accordance with the actor's competencies such as skills and experience to

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generate the value sought. The conceptualization of resource integration in S-D logic includes a network structure of resource integrating actors leading to value creations which is insight in the SSBA case. Through P4, this thesis explores the different types of interactions with resources an actor exhibits while exploring data to generate insights. Three types of resources which play integral roles in resource integration have been underlined in P4.

a) **Personal Competencies (PC)**: are intangible resources belonging to the principal actor involved in insight generation. They include business knowledge, technical knowledge, education, institutions (such as ideology, behaviour), and experience. In other words, any intangible resource the actor in an SSBA environment uses to perform an activity.

b) **Other Personal Competencies (OPC)**: same as PC, however, the 'other' refers to the actors, other than the principle, who are available in an SSBA environment to provide either business or technical support.

c) **Environment Resources (ER)**: are resources that are built upon technology to facilitate the insight generation. They constitute data, tools, and technology that are configured to support the actor independence in insight generation. It also includes all resources accessed through a computer or technological device such as documents organization rules and regulations.

Practically speaking, resource integration occurs throughout the process of insight generation. For example, to gather the needed data, business employees (actors) should have an adequate knowledge about the business domain, such as the type and timeliness of data relevant for the task. Then, they select a specific dataset using technological tools in conjunction with their technical expertise. During the user engagement, two types of resource integration exist, namely Linear and Clustered RI (see P4 for more details):

1) *Linear RI*: In direct resource integration, the enactment of environment resources occurs in a linear fashion. A business employee enacts a PC to interact with $ER_1, ER_2 \ldots ER_n$ until data insight is generated (see Figure 20). There are no specific rules on what and when certain resources are enacted because it mainly depends on an employee's PC. By linear, we mean that no support actor's OPC is enacted in such an interaction and the driver is only one actor and his/her own PC, which prevents the formation of a cluster, as we will see next in the clustered resource integration. This type of resource integration entails that there exists a fit between what the actor can do using PC and what the task requires to generate the desired outcome.

Hence, SSBA environment factors identified in P1 such as control, trust, autonomy, and independence are perceived and experienced by the user.
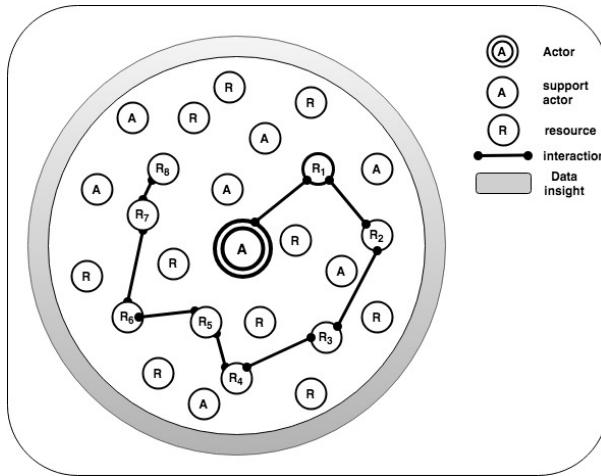
Figure 20:
Direct Resource Integration (from paper 4)

2) ***Clustered RI***: the actor's PC consists of technical skills, experience, and business knowledge, so the probability of requiring assistance in certain tasks cannot be neglected. In such a case, the enactment of resources does not follow a linear fashion but rather a nested one. The reason for the emergence of such a cluster is that there is an ill alignment between the actor's PC to carry on the task independently and ER. The ill alignment might be due to (1) a miss-fit between the actor PC and the resources needed to operate in order to accomplish the task at hand or (2) a miss-fit between the needed resources and the available ones in an SSBA environment. To elaborate more, OPC represents the competencies of other employees in an SSBA environment or what we refer to as support actors. Those actors in their turn can request assistance from ER, hence creating a cluster. The original actor does not have any control over the clusters and only receives the needed assistance by any means the support actor sees fit. Based on P4 empirical data, the two types of clusters, 1st tier cluster and 2nd tier cluster, are visualized in Figure 21.
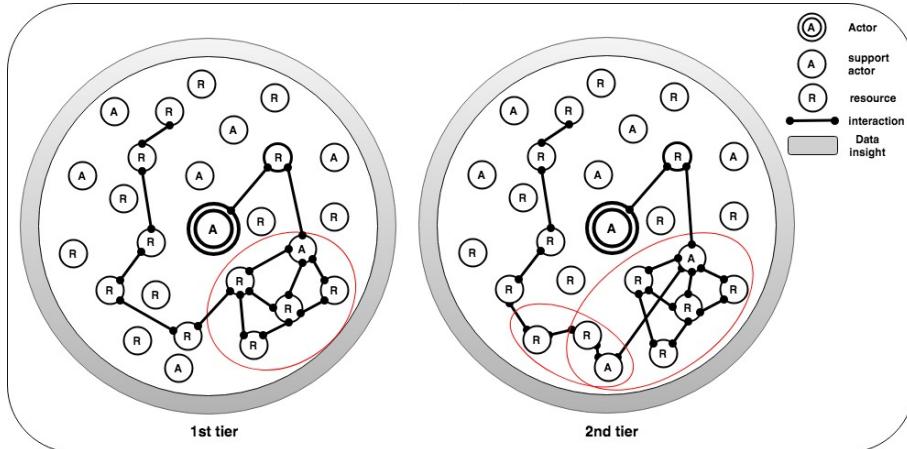
Figure 21:
Clustered Resource Integration (from paper 4)

The 1st tier cluster constitutes the direct support that a business user provides in case the initial actor lacks a specific business understanding or the techno-oriented user provides in answer to a technical question. In both cases, support is provided directly without the need to include more specialized people. This scenario is a direct result of ill alignment between the actor PC and ER during resource integration. The 2nd tier cluster emerges when the 1st tier cluster could not provide the needed support; thus, more specialized people are needed. In such a scenario, the support actors in the 1st tier cluster create a cluster on their own. Both scenarios are the empirical proof of the network nature of resource integration described in the process of value co-creation described by S-D logic (Overkamp et al., 2018; Vargo & Lusch, 2016a). In Table 18, a summary of each resource integration patters is presented in relation to S-D logic and its meaning from an organizational perspective.

Table 18:
Summary of resource integration patterns and their meaning

Resource integration pattern	Description – SD logic view	Implication - meaning
0-tier (direct)	The actor's institution, personal competencies (knowledge and skills) and SSBA environment (technology and data provided) are aligned and enable a self-governing value co-creation.	The ideal scenario where the user competencies are fully aligned with the SSBA environment resources, which results in full autonomy and independence.
1-tier (1 cluster)	The actor's institution or personal competencies (knowledge and skills) fall behind leading to the creation of a network. This network constitutes a part of the service ecosystem.	There is a miss-alignment between the users' competencies and the other resources provided in the SSBA environment. Organizations should provide training sessions and mentorship programs. By doing so, it reinforces the service ecosystem through self-adjusting and contained characteristics.
2-tier (2 clusters)	The SSBA environment lacks certain resources and requires improvements. It prevents actor from successfully integrating resources. This network constitutes a part of the service ecosystem.	The SSBA environment is still immature and prevents users from having a successful insight generation. Organization could re-evaluate the SSBA environment and unveil potential issues. By doing so, it reinforces the service ecosystem through self-adjusting and contained characteristics.

It is important to understand that either through a direct or clustered RI, the original actor develops the needed insights to make an informed decision. However, what is interestingly occurring is the inclusion of other competencies to interact with resources out of the original actor scope (see Figure 22). That is, the original actor possesses competencies that enable him/her to interact with a specific set of resources as shown in (A). As stated previously, analytical tasks are not trivial and sometimes may exhibit a complexity that forces the original actor to seek assistance and support. It implies that there exists a lack of specific competencies to generate the desired outcome. In such a case the original actor expands the competencies and resources used by including other actors' competencies to enact more resources as seen in (B and C).
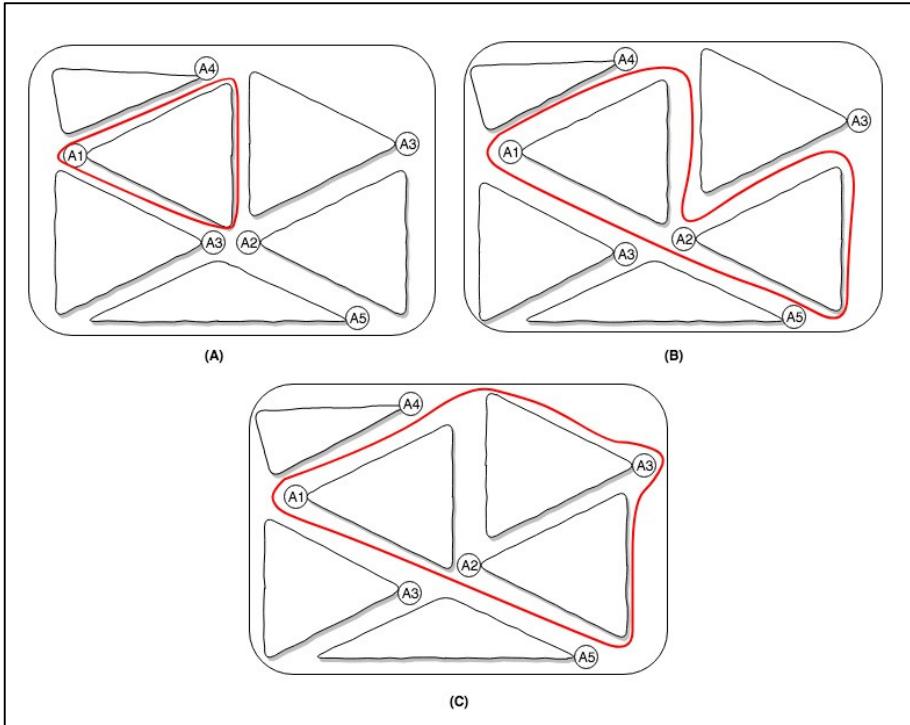
Figure 22:
Inclusion of others competencies

In summary, resource integration basically occurs by enacting a specific set of capabilities the user possesses in accordance with what the technological resource requires. As such, a balance must exist between three main resources, those being business users' competencies, environment resources, and support provided to integrate resources and co-create value. This activity results in two distinctive resource integration patterns characterized by the presence of a cluster or not. The direct resource integration is basically a non-dependent and autonomous business user exploring data and generating insights. The clustered resource integration is where users become partially dependent or fully dependent due to the imbalance between the user competencies and the ones needed to enact and interact with the SSBA environment resources.

6.3 Unexpected Findings

As previously discussed, the main premise of SSBA is to enable a more independent user during data analytics. I have described in Sections 6.2 and 6.3 how the appended papers (P1, P2, P3, P4) address the research questions and provide answers based on empirical data. It was interesting to notice that the empirical data collected also produced an important and unexpected finding namely "organizational agility" which was not a part of the research questions but considerably related to the value of SSBA and its impact at an organizational level. The appended paper "P5" argues that the independence of the user in data analytics does not only impact the user per se but also the ability of the organization to become more agile through two main dimensions: market capitalization agility and operational adjustment agility. Market capitalizing agility refers to a firm's ability to constantly look for areas to improve upon in their offered product or service and leverage on these to meet ever-changing customer needs (Lu & Ramamurthy, 2011). Operational adjustment agility, on the other hand, refers to a firm's ability to address their inner workings – distributed responsibility, data ownership and transparency across organizational units, etc. – as a foundation for responding to external changes (Lu & Ramamurthy, 2011).

The findings from P5 discuss four ways that SSBA supports the market capitalization agility and three ways how it supports operational adjustment agility (see Table 19). It is not the intention of this thesis to engage in a discussion about organization agility however it is considered a practical example of the value of SSBA in an organization. The importance of organizational agility is because competitive advantage is fleeting (D'Aveni et al., 2010), and any given organization needs to move faster in relation to its competitors and have the capacity to be flexible for the sake of effectively changing and adapting to new purposes and responding to emerging possibilities (Agarwal & Tiwana, 2015). Therefore, having the capability of organizational agility is fundamentally important (Lu & Ramamurthy, 2011).

Table 19:
Organizational agility and SSBA

Organizational Agility	SSBA enablement	
	What it enables	**How it enables**
Market capitalizing agility	Better understanding of supply and demand.	Through the diffusion of supply and demand needs to specialized units
	Fast response to requests	Through making each organizational unit capable of responding to user requests without any external reliance (IT/BI).
	More access and freedom to supply and demand navigation behaviour	By the exploration and exploitation of supply and demand data generated though the multi-sided platform (macro level)
	More access and freedom to traffic data and user clickstreams	By the exploration and exploitation of supply and demand data (micro level)
Operational adjustment agility	Nature of relation with the core unit	Through the independence of IT/BI department
	Empowerment	By the ability to create ad-hoc reports and analytics.
	Data access and usage	Through the ability to perform data mashup and exploitation/exploration data.

6.4 Concluding Remarks

The Self-service approach to business analytics relies heavily on two basic elements interacting with each other through the process of resource integration namely the SSBA environment and the user competencies. The more these two align with each other the more the user is independent during the insight generation hence fulfilling the promise of SSBA.

7 Discussion

Departing from the research aim and the two research questions, this chapter presents the overarching discussion from the theoretical and practical perspective. It also provides insights into research quality and concludes with a final reflection, limitations, and future research.

7.1 Theoretical Implications

As was established in chapter 2, the main BA value is focused on improving decision making through insight generation. Based on Seddon et al. (2017), the main trigger for insight generation is the use of analytic resources in organizations. The use of analytics resources requires users to interact and engage with available resources to generate insights. The more users are involved in such a process, the better decisions are made, hence more value from BA emerges (Seddon et al., 2017). In the same line of thought, S-D logic implies that value co-creation occurs when a network of resources integrating actors connected by shared institutions interact with several resources in a service environment. Building on that and through this dissertations' findings, the theoretical contributions are as follows.

The first contribution is the identification and description of the engagement modes that lead to insights. The Seddon et al. (2017) process model describes how BA value occurs in organizations that start by using analytic resources and finish with how the organization perceives the value of BA. This dissertation extends our understanding of how analytic resources are used by identifying three modes of engagement a user follows to process data into information leading to insights. In each mode of engagement, the user capabilities needed are identified and discussed in relation to the modes itself. By relating to Dinsmore (2016) categorisations of users in Section 2.2, SSBA further categorises information consumers based on their mode of engagement into three categories: high dependent users (mimic consumers), non-dependent

users (mimic analysts), and low dependent users (between consumers and analysts). In such a scenario, it is reasonable to consider that the non-dependent users are shifting towards the analysts in Dinsmore (2016) categorisation which leads to an increase of this category and a decrease in the number of users labelled as consumers. (this is how SSBA help in achieving a wide use of organization and enable a more data driven environment)

The second contribution is the identification of the resource integration patterns in each mode of engagement previously mentioned. It further theorizes resource integration by describing the patterns a user follows to either generate insights without creating any cluster (closely related to path 1 described by Seddon et al. (2017)), by creating one cluster to compensate for the lack of required competencies (closely related to path 1,2 described by Seddon et al. (2017)), or by creating more than one cluster to change or update the environment resources (closely related to path 3 described by Seddon et al. (2017)). Both paths 1 and 2 result in insights leading to decisions which result in organizational value. Path 3 in comparison directly affects the SSBA environment resources by optimizing, reconfiguring, and fine-tuning the SSBA environment, in which many users use to generate insights, supporting path 1,2. The system thinking and the self-adjusting characteristics of a service environment are evident in this case. This leads to the third contribution described below.

The third contribution is that this dissertation portrays SSBA as an approach to data analytics enabled by the presence of different analytical resources such as tools, technologies, and support to assist the user in achieving independence. All mentioned resources exist within a "self-adjusting" (Lusch & Vargo, 2014, p. 66) environment that is optimized and configured to support insight generation and informed decision making. As such, SSBA can reasonably be considered a service environment that enables independent data analytics and not a technology, capability or an extension of a BA solution. This is unlike other BI extensions or capabilities, such as mobile BI (Tona & Carlsson, 2013) and collaborative BI (Rizzi, 2011), where technology is the core element. The analogy between an SSBA environment and a service environment extends our understanding of SSBA and conventional BA. It is the actual interplay between the different elements in a self-adjusting environment, that is purposefully designed to support certain characteristics of independent insight generation. This also goes along with S-D logic service ecosystem thinking.

The fourth theoretical contribution is based on the fact that the DSS research stream is recognized for its multidisciplinarity. Researchers often borrow

theories from other disciplines or fields to describe or explore a certain phenomenon or the use of a DSS. For example, the construction of an "evolutionary DSS development methodology that uses cognitive bias theory as a focusing construct" (Arnott, 2006, p.55), expectancy theory may serve as the basis for theoretical explanation of the behaviour of users (De Sanctis, 1983), negotiation theories used as the basis for designing Negotiation Decision Support System (Jelassi & Foroughi, 1989), and self-organizing systems theory and demonstrate its application to problematic areas in Group Decision Support System (Contractor & Seibold, 1993). Consequently, this dissertation provides an empirical example of how S-D logic can be used as an analytical lens to explore and shed some light on phenomena related to DSS from a service environment perspective. Especially when DSS is becoming part of the organizational environment and is pervasively supporting a self-service approach to data analytics by lowering its operational complexity.

The fifth theoretical contribution is that, this dissertation uses S-D logic to provide a theoretical description and insights into the nature of SSBA by highlighting the importance of enabling a value embedded service through the cooperation and collaboration between the involved stakeholders. Resource integration is considered a core element in S-D logic since it depicts the actual engagement of actors with resources to co-create value. In the SSBA context, this dissertation theorizes resource integration in SSBA by identifying two main types of resource integration: linear and clustered, depending mainly on the pattern the actor follows to generate insights. The actor is either fully independent and does not require any support from other actors or at a certain point of time, a lack of cognitive abilities (skills, experience, knowledge, etc.) is perceived and support is needed.

The sixth theoretical contribution is to the S-D logic body of knowledge by identifying the modes of engagement that enable value co-creation with a special focus on resource integration in an empirical context. This is a response to a call for research on the need to develop a more mid-range theory to understand how different resources are integrated and value is generated in empirical settings (Vargo & Lusch, 2017).

7.2 Practical Implications

Business intelligence and analytics including SSBA is considered as one of the foundations of innovation, competitions, and productivity (H. Chen et al., 2012; Lycett, 2013; Sharma, Mithas, & Kankanhalli, 2014). Consequently, organizations are adopting such technologies to not only survive the competitive landscape but also to create an edge over other competitors. Accordingly, this dissertation provides practical contributions to better describe SSBA and provide some insights to practitioners as below.

1) ***An approach to data analytics***: many organizations realize the benefits of SSBA and its possible impact on business success, however, there still exists a vague understanding about its nature. Organizations perceive SSBA differently, for example; it could be seen as an extension to the traditional BI or a new feature and capability. This dissertation informs organizations about the intangible nature of SSBA and highlights the importance of the institutions whether at the individual level or at the organizational level. It depicts SSBA as an approach to data analytics that is controlled and governed by several factors such as the trust, control, and support over the insight generation, as well as employee skills needed to operate the tools and technologies provided. This thesis also highlights the importance of technology in such an approach, however the critical aspect of SSBA is the readiness of the employees and their capabilities to excel and become active members in such an environment. Therefore, organizations are advised to first understand the capabilities of their employees and their readiness to participate in such a shift and endeavour to better serve themselves.

2) ***Information authorship:*** when a service system is in place, it has the capacity to change the way things are done. We saw examples in P1 and P2 on how the Internet banking and online booking systems have impacted the relationship between organizations and their customers. Such change also happens to employees in SSBA. They become more in control of their demands and decrease their dependence on technical people, which, in turn, changes or shifts their role from consumers of information provided by technical people to authors of their own information. As a result, organizations gain a better understanding of the impact of SSBA on the employees themselves and will support this shift. It also implies that the responsibility of employees has grown since they assumed a new role, which also changes the role of the technical department from being a controller to more of a controller/enabler in supporting data analytics. As

such, organizations are advised to support these role and responsibility shifts and to also expect changes in the routine process and possibly the actual structure within departments.

3) ***Criticality of setup phase:*** even though this thesis sees SSBA as an approach to data analytics, it also acknowledges the importance of technology and the way it is set up and optimized to provide a value-embedded service (in terms of data) to its users. In P2 the process of building SSBA is described and the importance of the setup phase (co-production) is highlighted as a portal for building valuable service for employees. It stresses the importance of involving business employees when creating data models. Building on that, an organization can invest more in such a phase to provide a more comprehensive service and concrete infrastructure for SSBA.

4) ***Steps to solve an analytical problem:*** one important question for organizations is how users solve an analytical problem or explore an opportunity in SSBA. This is not a trivial process but rather more complicated than we think. P3 illustrates five major iterative steps (data gathering, preparation, analysis, visualization, and interpretation) answering the mentioned question. Each step is considered a process that requires certain capabilities from employees to produce results for the next step.

5) ***Capabilities needed in SSBA:*** as previously discussed in point 4, the process of solving an analytical task includes four steps. Each step requires the employee to possess a certain set of skills in line with what the step requires to produce an outcome for the subsequent step. P3 highlights those needed skills or as they are referred to, as "capabilities" (see Table 14 in Section 5.3). Those capabilities are not just technical but also analytical (such as descriptive analysis, regression, and variance) and creative (such as creative visualization, dashboards, and interpretation of results). Such a classification provides the organization with the basic illustration of what employees need to have in order to engage in SSBA environment independently, hence they can plan strategies and take actions accordingly. As such, organizations are advised to survey their employees to understand first their capabilities and potential to be able to decide whether they are ready for independence and autonomy or if they are not mature enough.

7.3 Reflections on Research Evaluation

In this section, the measures to ensure good quality of research are addressed. Klein and Myers (1999) have developed a set of principles not only to guide researchers in conducting interpretive research but also to evaluate them. Several studies have employed those principles as guidelines evaluating interpretive research in the IS field (Åkesson, 2009; Boudreau & Robey, 2005; Jonsson, 2010; Pikkarainen, Haikara, Salo, Abrahamsson, & Still, 2008). As such, building on the previously mentioned principles in Section 4.1 below, is a reflection on how those principles were applied to this research.

The Fundamental Principle of the Hermeneutic Circle: The hermeneutic circle implies that a new understanding of the whole fundamentally relies on understanding the individual parts, and in turn, the individual parts can only be understood with reference to the whole in an iterative process (Klein & Myers, 1999). To develop a deeper understanding of how SSBA enables and supports user independence and autonomy, it was first important to explore what constitutes an SSBA environment and how resource integration occurs to generate insights. This is a rather iterative process between different sources of evidence such as empirical data based on interviews, field observations, and documents.

The Principle of Contextualization: The research context of this research is SSBA in an organization. In Section 4.2 of this dissertation, a detailed description of the case under investigation is presented including a short historical overview of the investigated organization and how the organization's need for data analytics led to the adoption of SSBA.

The Principle of Interaction Between the Researchers and the Participants: This research collects data from three sources of evidence: interviews with participants in their normal settings, field observations, and documents. Most of the interaction occurred during the interviews as it included showing examples, cases, past problem and solutions in relation to data analytics in the SSBA environment. It also included informal sessions over coffee and lunch where the participants were somewhat more talkative about certain topics. This improved my understanding of the context, the SSBA environment, and the interaction between users and technologies.

The Principle of Abstraction and Generalization: Having started this research with an exploratory mindset in an effort to gain more understanding about the context, gave me the opportunity to be flexible without previous

assumptions. This exploration guided me to choose the concepts that were appropriate to collect and interpret the data. For example, after several field visits and while observing users in their natural environment, I have realized that an SSBA environment fundamentally mimics a service environment where the IT/BI department provides and maintains a service that users use to serve themselves and gain agility in fulfilling their tasks. Based on such a depiction of an SSBA environment, I have applied the S-D logic to further explore how resources are integrated to generate value. Walsham (2006) mentions four ways of generalizing through concepts, theories, specific implications or rich insights. In this research, generalization was done by introducing new concepts and specific implications as will be discussed in Chapter 6.

The Principle of Dialogical Reasoning: During the literature review and exploration of many journal articles and industry white papers, a kind of conception about the nature of SSBA led to several in-depth discussions with co-authors about the real nature of SSBA, since the findings suggested a rather different conception. This was especially true in regards to what it means for a user to be independent in data analysis and how resource integration occurs. Hence interpretations in this research were not only limited to theoretically informed concepts, but also open for new ones.

The Principle of Multiple Interpretation: Since different participants from different departments were interviewed and asked similar questions, it is only logical that different views of the same topic investigated will arise. Those interpretations are of value as they portray and provide insights about SSBA from both technical and business perspectives.

The Principle of Suspicion: To be critical while looking at the data, verification between different sources of evidence was important. For example, reading scientific and industry material about certain concepts mentioned during the interviews, or investigating the meaning of certain expressions used during the interviews like 'data as instinct' or 'data in our spine'. Also, follow-up questions were sent to participants through emails and short follow-up interviews through Skype.

All seven principles collectively present an effort to describe how good quality research was maintained. Indeed, questions can always be asked, and quality can always be questioned, however, those principles are well established among IS scholars for evaluating interpretive research.

7.4 Limitations

As with all research, the results presented in this research are neither the absolute truth nor without flaws. As such, the contribution of this research needs to be considered in view of the following limitations.

First, since this thesis adopts an interpretive case study, it inherits a limitation in relation to replication. Even though I have described the research process with transparency, it is still challenging to replicate (Wiersma & Jurs, 2005) because not only is it seen from the researcher understanding and interpretation, but the case study also targeted a specific industry (digital marketplace).

Second, it is also difficult to make causal inferences from case studies mainly because it is challenging to rule out different explanations. The generalization of the findings of a case study is also problematic as it is the interpretation of the chosen context and the fact that it involves the behaviour of one person, group, or organization (unit of analysis). The behaviour of the unit of analysis may or may not reflect the behaviour of other similar entities in other contexts. Hence, this thesis may only be suggestive of what may be found in similar organizations.

Third, this thesis did not consider the impact that the culture may have on the findings. The empirical data was collected in Norway, which is well known for its technological and societal development and most likely the findings of this dissertation are only valid for a context that is similar. In other words, the findings will probably vary if the data was collected in a developing country where employees are less quantitative driven and more intuition oriented.

7.5 Future Research

Based on the topic investigated and following the research question, this dissertation starts with a broad perspective by investigating the SSBA environment in organizations then narrows down to the actual engagement of the users with resources to generate insights for decision making. Several important concepts have been explored such as "resource integration" that occurs between the SSBA user and the "resources" in the SSBA environment. As such, this thesis sets the stage for future research direction.

First, on a fundamental level, resource integration occurs through the interaction between Actor-Resource (A-R), Actor-Actor (support) (A-A) or Resource-Resource (R-R) or any configuration leading to insight generation as we explained in Section 6.2. What remains unexplored is a more in-depth investigation of the mechanisms of interaction between the A-R, A-A and R-R.

Second, future research may extend the current findings and decontextualize the case study by a more general view of using analytics and surrounding data in everyday life with a focus on individuals outside an organizational setting. In other words, how regular people use the surrounding data to make daily decision about their lives. This entails how they choose which airline to fly with, what credit card to use, when to buy a certain product or service, and when to sell it and so on.

Third, this dissertation explored Seddon et al. (2017) process model of BA value and did not explore the variance model presented. Future studies might also explore the variance model in the context of SSBA.

Fourth, since the ecosystem perspective of SDL was not deeply addressed, future studies might explore this avenue and how the self-adjusting and self-containing mechanisms occur in an SSBA environment.

Fifth, choosing a different data collection method may yield varying results. For instance, if a quantitative perspective confirms, disapproves the findings, or reveals another unexpected viewpoint.

8 Conclusion and Final Reflections

We cannot ignore the fact that we are becoming more and more computer literate and driven by facts and numbers. However, a simple question yet fundamentally important needs to be asked 'is this always advantageous to us?' On the one hand, numbers tell us a quantitative story and present us with facts and figures that reduce (if not remove) the level of uncertainty in our decision making. On the other hand, that makes us more like Artificial Intelligence (AI) and robots where all decisions are based on algorithms and data that may disregard our human side and what is called 'gut feelings'.

We, as consumers, and before purchasing any goods, engage in our own rather simple market research using our phones, computers, and other devices to identify the best options available. This is also reflected inside the organizations where employees explore available data to make the best-informed decisions. SSBA is not a technology, tool or a capability of certain technology. It is rather an approach to data analytics that is enabled by the data driven ideology and an optimized organizational environment. We cannot disregard the importance of the triadic relationship between the user, technology and institutions in SSBA environment. We also cannot rush into adopting SSBA in an organization. We first need to check whether there exists an alignment between what SSBA needs to succeed and what the organization possesses.

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Appendix

Interview guides

First round of Interviews:

Category	Interview Guide
Demographic information:	Can you state your name position and years of experience? What is your education background?
Current users	What do you do exactly at Finn.no? What is tableau? How tableau helps you? What made you use tableau? How and when do you use tableau? How easy is to fulfil your needs using tableau? Do you have any issues when it comes to tableau? How often do you use tableau? What is the value of tableau to you? (What it benefits you) Did tableau change your way of working? (Is there a change in the way you use to do things?) What do you do with the data from tableau? Is there any difference between before and after tableau in terms of waiting for reports? How often do you need assistance in using tableau? Do you use other tools with tableau? Would you rather create your report by yourself or ask somebody to do it for you?
Prospective users	Why you did not use tableau till now? Do you need tableau to help you? Would you rather create your report by yourself or ask somebody to do it for you? Do you use other tools than tableau to help you do your work?
Technical users	What issues did you face when implementing tableau? How tableau is managed? What strategies did you employ to push users to use tableau? In case of having different strategies, is there any timing regarding when to use what? Do you have any policy regarding tableau? How do you support the adoption of tableau? How do you control this adoption? How often users ask for your assistance in creating reports? How often you are asked to modify the model? Do you have a visual architecture of the SSBI?
C level	Can you tell me a bit about yourself and your experience? What is your stand on the data driven ideology of an organization? What role this ideology plays in the digital marketplace business? How do you promote this ideology, do you have any strategy? Do you think that Finn business is complex? Can you explain why it is complex? What is the importance of BI in Finn business? What about the self-service capability? What are the challenges associated with a digital marketplace and how does SSBI helps in addressing them? How BI (tableau) has affected Finn financially? Do you notice any changes? If we make a cost-benefit analysis on tableau, what would out-weight what? Is there any causality between having tableau and the number of users of the platform? I have noticed that you are responsible of the insight department, why you? Shouldn't be the CTO? Is there any question you want me to ask you?

Second round of Interviews

Category	Interview Guide
Demographic information:	Can you state your name position and years of experience? What is your education background?
Theme 1: Resource integration	How important is the data in your daily activities? And what do you mean by that? How do you use the data in your work? Give example please? How do you start exploring the data to answer a question or fulfil a task? Give an example please? What makes you effective in using the tools and data available? What can affect this process? Are those tools easy and appropriate to use? How do you use the different tools available? Can you give me an example? How often you need external help (IT or friends) when analysing data? At what point is that support crucial? Do you collaborate with colleagues or ask help? Can you rate the following skills based on your level of knowledge? Do you need all those skills to fulfil a task? Which skill you think you need to develop more? What are the most important skills you have and why they are important? What could prevent you from fulfilling a task?
Theme 2: Service exchange	What is the goal for your engagement with data? What do you expect in return? What benefits you provide for your department, customer and FINN? How do you think your work affect FINN customer? How do you think your work affect FINN service platform (FINN website)? What is your role in the business cycle FINN has? What do you get from working in your current position? Usually what kind of knowledge do you need when working with data? To finish a task, beside your knowledge, what else do you need? Example? In case you need support, what type of support is that? When and whom do you ask for it? (External support)
Theme 3: Institutions and institutions arrangements	How would you describe the environment at FINN? (Organization culture) Did you face any problems when you first came in terms of work routines? (Shared in institutions) Which do you prefer more numbers or text and why? (Values and beliefs) Do you feel more comfortable in working with certain people? Why? (Social structure) To what extent the environment at FINN affect your way of work? (Innovation procedure) Do you feel frustrated when you ask for support? How often do you participate in meetings to improve the way you analyse data? How often do you attend trainings? Is there any rules, documents or information on what to do when you have difficulties in analysing data? Do you feel enough support? In what kind of ways is it coming? How can it be improved? How often do you ask for support and how quick you get help? If you are not satisfied with support to whom do you complain?

Analytical skill set guide– secondary data

Area	Base	+1	+2	+3
Data gathering	• Can use Tableau prebuilt dashboards. • Do not know which sources to use when. • Unable to make source quality assessments.	• Using published data sources. • Can identify possible sources. • Has an idea about FINNs data-model and what it covers. • Can make some source quality assessments.	• Create data sources. • Define surveys. • Make critical selection of sources based on pro/cons. • Understands FINNs data model. • Ability to use secondary sources for context.	• Combine data sources. • Make source selections based on data quality vs use case (can make trade- offs). • Contribute to data collection quality improvements.
Data preparation	• Pre-made calculations.	• Using measures and dimensions (defined metrics). • Identify missing /skewed data.	• Define measure / dimensions. • Indexing. • Outlier handling. • Correct missing / skewed data.	• Cross source calculation. • Can use any tool according to objective.
Analysis	• Open Excel and look at tables.	• Sum, grouping, average.	• Median/percentile descriptive, filtering, outlier handling. • Elementary A/B testing.	• Standard deviations, variance, regressions, confidence intervals, stat significance. • Know A/B testing boundaries Test = hypothesis.
Documentation	• N/A.	• Saving for future reference (own).	• Share to peers, (includes steps to reproduce).	• Publish to peers, includes steps to reproduce. Includes SQL or source code.
Presentation	• Copy from Excel -> PPT.	• More advanced PPT/PDF from multiple sources.	• Visualization published on Tableau server Create reports in Adobe.	• Create dashboards in Tableau Shared Ad Hoc reports in Adobe.
Tools	• Basic Excel. • Tableau server reports. • Adobe reports.	• Tableau server/Tableau-hub self-service. • Adobe workspace. • Intermediate excel (formulas, filtering).	• Tableau desktop. • Adobe ad hoc. • Advanced excel (macros, advanced formulas).	• Dashboards. • SPSS. • R. • SQL.
Analytical problem-solving process	• No clue where to start. • Don't know which method to use.	• Vague idea how to proceed, asks Insight or repeat previous effort, can't fully differentiate between (or use) falsifying and supportive evidence, some idea about methodology	• Ability to break down the problem into hypothesis, ability to plan testing of H Can diff between falsifying and supporting evidence, can choose methodology.	• Ability to evaluate and interpret findings and suggest further testing or action (including experiments from start to finish).

Non-disclosure agreement

DECLARATION OF CONFIDENTIALITY AND NON-DISCLOSURE

This declaration of confidentiality and non-disclosure (**"NDA"**) is submitted by [Company name, a [nationality] [limited liability company] with business registration number [   ] (**"Recipient"**) to the benefit of Schibsted ASA, a Norwegian public limited liability company with business registration number [   ] (**"Schibsted"**).

1   PURPOSE AND PROJECT

The purpose of this NDA is to establish provisions of confidentiality and non-disclosure relating to information proprietary to Schibsted and/or its affiliates which comes in the possession of the Recipient in connection with [the Recipient's potential engagement as consultant to Schibsted] (**"Project"**).

2   CONFIDENTIALITY AND NON-DISCLOSURE OBLIGATION

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2.2   No Use

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Imad Bani-Hani[a], Olgerta Tona[a], and Sven Carlsson[a]

[a]Department of Informatics, School of Economics and Management at Lund University, Lund, Sweden

ABSTRACT

Self-Service Business Intelligence (SSBI) enables business users, such as executives, managers, analysts, and knowledge workers to build reports on a need-basis to support their decisions and actions toward business success. This suggests that business users are empowered not only to consume information but also to author it. Yet, research on SSBI is mainly concentrated at the industrial level, and furthermore little is known on the way SSBI is changing the current state of BI. To address this lack of knowledge, this study explores the attributes of SSBI that are necessary to extend the role of a business user beyond that of an information consumer by drawing on the literature of Self-Service Technologies (SST). This study provides a new definition of SSBI as a new approach to BI. Furthermore, it highlights the duality of high levels of co-production and low levels of dependency as key to the SSBI approach.

Introduction

In 2010, eBay, an American multinational corporation and e-commerce company, changed its data warehousing strategy. Through cooperation with Teradata—an international computer company that sells analytic data platforms—eBay extended the functionality of its Enterprise Data Warehouse (EDW) to support data experimentation and analytics for its employees. Through this extension, business users, in particular, could create virtual data marts, which are effective in transferring new discoveries from the testing environment into production because of a high cost-effectiveness and time efficiency. Consequently, business users can perform a variety of experiments, such as developing and testing hypotheses about eBay's interface and its impact on the sellers' strategies. As the case of eBay illustrates, business employees are incentivized to independently get involved in business analytics processes of organizations, given that they have access to data and "adequate" technological tools. (Goul 2011).

Closely related to Business Analytics (BA) and often used interchangeably, Business Intelligence (BI) is "a broad category of applications, technologies and processes for gathering, storing, accessing and analyzing data to make better decisions" (Watson 2009, 491). In addition to the impacts of BI on the decision-making process (Goul 2011), research also shows that when used at both managerial and operational levels, BI can generate value in business processes and organizational performance (Kowalczyk, Buxmann, and Besier 2013; Popovič et al. 2012), such as improvements in strategic planning and alignment (Elbashir, Collier, and Davern 2008).

Similar to other technologies, BI systems are continuously advancing. The introduction of Hadoop clusters in BI infrastructure, in response to the big data era (Shanks and Bekmamedova 2012), and the emergence of mobile BI in response to the advancements of mobile computing (Phillips-Wren and Hoskisson 2015) illustrate some of the recent developments. Equally important,

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BI is striving to cater not only to business analysts—as the primary users—but also to other business users across the organization. To this end, BI capabilities are enhanced so that it provides to executives, managers, and knowledge workers not only customized data access but also the possibility of building reports on a need-basis with the ultimate aim of supporting decisions and actions for business success (Tona and Carlsson 2013). BI that provides self-service capabilities to its end-users is known Self-Service BI (SSBI).

Industry plays an influential role in promoting self-service capability as the main competitive advantage of BI and support organizational agility (Bani Hani, Deniz, and Carlsson 2017). SSBI is at the forefront of other current BI trends such as collaborative BI (29%) and mobile BI (18%) (Weber 2013). An industrial study (led by enterprise software industry analysts) reported that users appreciate the BI self-service capability with 55% of BI users (in organizations) who engage in self-service tasks and 24% who are planning to do so in the future (Barc 2014). These reports highlight the task accomplishment independence as a major impact of SSBI use, because users are able to build or design their own reports even when multiple data sources are involved (Barc 2014).

To move toward a data-driven strategy, organizations are striving to democratize the process of data analyses across levels so that all employees are involved in the data analytics process (Barc 2014). In line with this recent movement, SSBI has emerged as a way of shifting the role of business users from information consumers to information authors. However, SSBI potentiality remains at the level of assumptions and suggestions because its nature is dominated by confusion. Even though BI is widely spread in organizations (Patil 2011), little is known on the way SSBI is changing the current state of BI and the way it can further support organizations being data-driven.

Therefore, the aim of this article is to explore SSBI and investigate the main components that are necessary to expand the role of business users from information consumers to information authors. This study draws on the literature of self-service technology (SST) for two main reasons. First, SST is an umbrella term for technologies that offer self-service capabilities. Because SSBI is being promoted, sold, and bought by companies with the premise that it provides self-service capabilities to its business users, we argue that SSBI falls firmly under SST. Second, SSBI is an interesting instance of SST because it operates inside organizations rather than outside as most SSTs do.

The contribution of this research is two-fold. First, through an SST literature review, this study provides an improved definition of SSBI. Second, by shedding light on SSBI, hopefully, organizations will make better sense and consequently better decisions regarding the adoption of SSBI.

The article is structured as follows. We first define SSBI in relation to BI and describe the current state of SSBI from a practitioner and academic perspective. We then discuss in details the literature review process of this study. We subsequently present the findings, and finally, we conclude the article by discussing the implications and conclusions of this study.

From BI to SSBI

In BI, a broad category of tools are used in order to gather, store, access, and analyze business data (Arnott and Pervan 2014). During the data gathering process, BI tools connect to a variety of internal and external sources (Watson 2009), e.g., enterprise resource planning (ERP), customer relationship management (CRM), supply chain management (SCM), and other legacy systems. Further, data is extracted, transformed, and loaded (ETL) (Gibson and Arnott 2005) and stored in data warehouses, data marts (Gibson and Arnott 2005), or recently to Hadoop clusters (March and Hevner 2007; Watson 2009). After data storage, data is available to be analyzed and through a variety of analytical tools is converted into information. Users, via different devices such as a PC, laptop, or mobile device, can access information to derive knowledge necessary for decision-making and action-taking.

From a BI perspective, recent research points out three main types of user: business users (basic and domain-based skills), business analysts (more analytical skills on how to build ad hoc reports and what-if scenarios), and data scientists (mathematical and statistical skills) (Phillips-Wren et al.

2015). In a typical scenario, business users consume information that is made available to them by business analysts, through a request or based on a regular agreement between departments. Hence, through BI they consume information, which they then convert into knowledge based on their intuition, previous experience, task, and context to be able to take decisions and actions. Interestingly, in this phase, BI supports a business user only during information use.

SSBI that has emerged as a new approach to BI has the potential to expand the involvement of business users allowing them not only to consume information on BI but also to author information. To this end, they can independently access data and produce information in the form of reports and simple analytical queries without relying on business analysts or data scientists who typically are part of an IT/BI department (Phillips-Wren et al. 2015). However, how an SSBI supports a business user to participate in the conversion of data into information is still unknown given a lack of academic research on SSBI.

Current state of SSBI

The past decade has witnessed a big change in services, such as the transformation from non-digital services to digital services (Abbasi, Sarker, and Chiang 2016). The role of technology in allowing information to be repackaged and transferred has led to new opportunities for service exchange and innovation (Yoo, Henfridsson, and Lyytinen 2010). In addition, technological advances have focused on self-service options and capabilities to improve the way services are delivered. Software vendors are striving to follow this movement by entailing a self-service dimension into their BI products. Table 1 lists some industrial and academic attempts to define SSBI.

Schuff et al. (2016) refer to SSBI as a facility within the BI environment, Imhoff and White (2011) and Gartner IT Glossary describe it as a BI system, and Weber (2013) labels SSBI as an ability. There is no clear definition of SSBI. So, what exactly is SSBI? Is it a capability within the BI environment, does it represent a new system, or is it a new approach to BI? Is SSBI viewed from a technological lens or do users play a more important role in defining SSBI?

Tracing back technologies that afford self-service capabilities, they have been grouped as Self-Service Technologies (SST) by extensive studies throughout the years. SST is defined as: "the technological interface that enables customers to produce a service independent of direct service employee involvement" (Schuff et al. 2016). In addition, Meuter et al. (2000, 50) define SST as technology based self-service (TBSS) to denote the activity or benefit built on hard technology that a service provider offers to customers to perform their service requests fully or partially by themselves. SST emphasizes the technology itself whereas TBSS focuses on the activities performed directly or indirectly by the customer

Table 1. current definitions of SSBI.

Reference	Definition
Imhoff and White (2011), Poonnawat and Lehmann (2014), Lennerholt, van Laere, and Söderström (2018)	The facilities within the BI environment that enables BI users to become more self-reliant and less dependent on the IT organization
Gartner IT Glossary (n.d.)	Is a form of business intelligence (BI) in which line-of-business professionals are enabled and encouraged to perform queries and generate reports on their own, with nominal IT support. Self-service analytics is often characterized by simple-to-use BI tools with basic analytic capabilities and an underlying data model that has been simplified or scaled down for ease of understanding and straightforward data access.
Weber (2013), Watson, Wixom, and Yen (2013)	Is a BI system that enables business executives, managers, operational decision makers, analysts, and knowledge workers to access the information they need whenever and wherever they need it, providing key data to support the decisions and actions that are critical to business success.
Corral et al. (2015), Schuff et al. (2016)	Is the BI ability to give business users access to selection, analysis, and reporting tools without requiring intervention from IT

in order to receive a service (Wang and Namen 2004). Interestingly, these two definitions target a customer-business relationship, ignoring the instances SST can be used within an organizational setting. Furthermore, an SST is sometimes described based on its application and context, such as internet-based self-service technology (ISST) that denotes an SST that operates using internet (Wang and Namen 2004).

At an abstract level, SST and SSBI have some similarities. For example, in SST the firm manages a service offered to customers to complete a task themselves. Similarly, in SSBI, the IT/BI department creates and manages a service platform (SSBI) to be used by the organization's employees in servicing themselves. However, on a detailed level, in SST the customer tries to accomplish a certain well-defined task through self-service (e.g., in online banking), whereas with SSBI one tries to draw conclusions and make business decisions based on data analytics, information extraction, etc. (Schultze and Orlikowski 2004). Wrong or uneducated self-service steps in the data selection and processing will likely lead to wrong business decisions. Due to this similarity and the richness of SST academic recourses, this study draws on SST literature to improve the current definition of SSBI and outline the necessary attributes that shift users from a consumer to an author.

Method

To achieve the aim of this research we conducted a systematic literature review (see to Figure 1) following rigorously methodological guidelines in order to ensure validity and reliability (Imhoff and White 2011).

Scope of the review

As mentioned above, the focus of our review is the investigation of SSBI by drawing, to a large extent, from the SST literature. The aim is to explore the main characteristics of SST and its outcomes, which will later be transferred and adapted to a BI context. To this end, we pre-defined some categories such as: research method, internal/external use of SST, context, IT artifact involved, SST definition, and the main research contribution for each article. Furthermore, we delineated the target audience for this study: namely research focused on BI and particularly in its self-service capability together with practitioners struggling to understand more about SSBI.

Identifying search terms and database sources

Prior to our final literature search, we quickly explored the SST literature to gain a preliminary understanding of the domain. Consequently, we aimed to derive meaningful search terms in order to maximize their effectiveness during the search process (Brocke et al. 2009; Webster and Watson 2002). Three main SST acronyms were deemed suitable to be used for the final literature search: Self-Service Technology (SST) (Brocke et al. 2009), Internet-Based Self-Service (ISST) (Meuter et al. 2000), and Technology-Based Self-Service (TBSS) (Schultze and Orlikowski 2004).

As part of a test phase, we used these three terms in an explorative database search. The initial results were used to fine-tune the search criteria. In our first test, we observed that many articles only mentioned the aforementioned search terms without further elaboration, thus being far from the
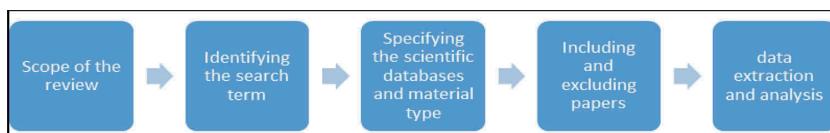
Figure 1. Process of literature review.

focus of this study. Instead, we decided to apply our search terms only to the title and abstract of journal articles. The logical operator "OR" was used to include all results from the three acronyms resulting in the below search criteria.

(AB "self-service technology") OR (AB "Internet-Based Self-Service") OR (AB "Technology-Based Self-Service") OR (TI "self-service technology") OR (TI "Internet-Based Self-Service") OR (TI "Technology-Based Self-Service")

One important step in the literature search was to identify the main scientific databases as data sources. The following databases were selected as our data sources mainly because they comprise a relatively comprehensive number of quality journal articles: EBSCSOhost (Business Source Premier and Econlit), Science Direct, and Scopus® (Figure 2: scientific database selection step). These databases collectively contain the top-ranked journals (basket of eight) stated by the College of Senior Scholars: European Journal of Information System, Information System Journal, Information System Research, Journal of AIS, Journal of Information Technology, Journal of MIS, Journal of Strategic Information Systems, and MIS Quarterly.

Inclusion and exclusion of articles

Due to the large number of search results, the authors agreed and made critical decisions on what kind of studies should be included or excluded in the review (Scherer, Wünderlich, and von Wangenheim 2015). Because this literature review aims to maintain comprehensiveness, studies that had SST at its core and contribute to the understanding of the phenomena have been included. Also, industry reports such as (Sterne, Egger, and Davey Smith 2001) have also been considered. Furthermore, no selection filter was applied to research methods employed in the studies. The exclusion criteria were specific as the area of SST can be very diverse due to its nature of combining different disciplines such as: service provision, marketing, technology, and human interaction design. The studies that dealt merely with aspects related to the human-computer interaction area (design, interface), architecture, and implementation were excluded. Also, studies on the validation and verification of a certain SST have been excluded, as being not in line with our study goals.

The first search in the abovementioned databases resulted in 838 different academic publications including journal papers, conference proceedings, magazines, reports, reviews, books, and trade publications. By specifying the three scientific databases mentioned earlier, the number of academic publications decreased to 328. After selecting only journal papers, the number decreased to 206 academic journal papers. This number decreased to 143 after removing duplicated material. Applying the inclusion and exclusion criteria the final number of papers selected for our review was 81 (for more details on the process refer to Figure 2).
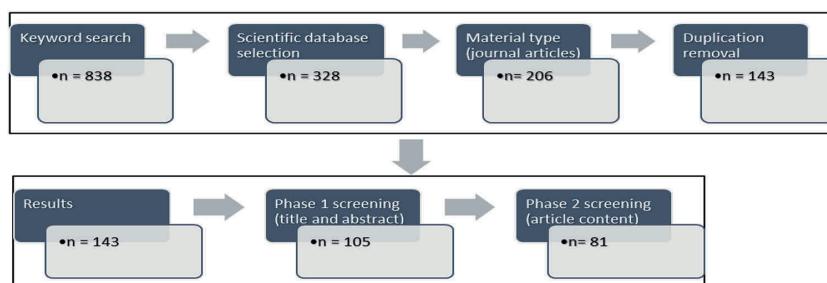

Figure 2. Selection process.

Data extraction and analysis

The information extracted from these articles was organized in a table containing information related to the bibliographic facts, the context of the study, research contribution, the nature of the IT artifact, and its use—either internal or external—from an organization perspective; dimensions pre-defined during the review scope phase. After the fields of the dimensions were filled in for each individual paper, further analysis of the text under the category of research contribution took place. At this point, the author and co-authors were involved independently in the coding process (see Table 2). Following an extensive discussion where authors presented the rationale behind their choices, the results showed a match in terms of codes and sub-codes, which enforces the internal coding reliability. Later, codes and sub-codes were edited, merged, and deleted based on an agreement between the authors.

Findings

Our results suggest that SST publications have gradually increased, especially in the last decade (see Figure 3). 1994 denotes the year of the initial research on SST followed by a relative dramatic increase directly after 2004. We believe that this corresponds to the era of service digitalization where organizations seized the opportunity to enhance customer satisfaction, retention, and return of investment.

Furthermore, SST is widely researched and published in different disciplines outlets (as shown in Figure 4). Unsurprisingly, the top publication outlets correspond to Service and Management, whereas Information System and Management occupy only 3% of the total. This goes hand-in-hand with the fact that 92% of journal articles focus on the external usage of SST (business-customer relationship) and only 8% investigate SST inside organizations.

In terms of method used, quantitative methods (including experiments and surveys) are leading. Qualitative research follows after, but with a huge gap compared to the quantitative methods (see Figure 5).

Through the SST literature review, we have identified five main attributes that characterize and contribute to the success of SST. In Table 3, we list the five attributes and also provide some key references in connection with them.

Table 2. coding example.

Source	Author 1 sub-code	Author 2 sub-code	Adopted codes
Shamdasani, Mukherjee, and Malhotra (2008)	Trust, convenience, perceived control, discomfort, insecurity,	Task complexity, trust intention, fun, technology anxiety, control over tech.	Trust, Control

Figure 3. Published SST journal articles since 1994.
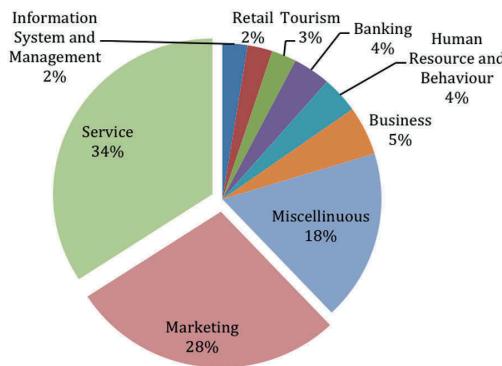
Figure 4. Disciplines publishing SST articles.
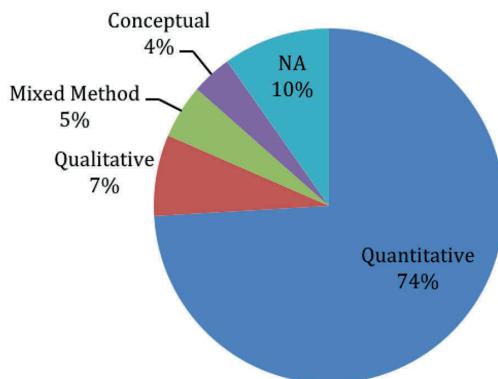
Figure 5. Research method overview.

Table 3. example of articles.

Concepts	Example of articles
Co-production	Imhoff and White (2011); Collier and Sherrell (2010); Eastlick et al. (2012); Hilton and Hughes (2013); Ding, Verma, and Iqbal (2007); Lanseng and Andreassen (2007); Lin and Hsieh (2011); Schuster, Drennan, and N. Lings (2013), Turner and Shockley (2014)
Autonomy	Hilton et al. (2013), Robertson and Shaw (2009), Oh, Jeong, and Baloglu (2013)
Ease of use	Liu (2012), (2013); Anitsal and Paige (2006), Eastlick et al. (2012); Evanschitzky et al. (2015); Hsiao and Tang (2015); Kim et al. (2014)
Control	Narteh (2015); Dabholkar and Spaid (2012); Oghazi et al. (2012); Shamdasani, Mukherjee, and Malhotra (2008); Zhu et al. (2007)
Trust	Oh, Jeong, and Baloglu (2013); Buell, Campbell, and Frei (2010); Collier and Kimes (2013); Dimitriadis and Kyrezis (2011); Lee (2016)

Co-production

Co-production, also referred to it as co-creation by some authors, denotes the process in which a customer use a firm's proposed service and integrates it with his or her personal resources (skills, knowledge, time, etc.) to generate personal benefits, which is highly subjective to the beneficiary (Oh et al. 2013). The process of co-producing makes the customers share responsibilities in producing

the needed service (Vargo and Lusch 2008; Vargo, Maglio, and Akaka 2008), and the level of the customer's co-production increases through the transfer of the employee task to the customer (e.g., internet banking) creating a so called "partial employee" (Eastlick et al. 2012). The use of an SST also minimizes the interaction between a customer and an employee. Organizations aim toward this strategy because of cost reduction and employees' time efficiency. However, the degree to which a customer ignores the human intermediary depends on the complexity of the service. A high service complexity with a high need of cognitive abilities will make an SST less attractive (Baron, Harris, and Hilton 2009; Jo Bitner et al. 1997), therefore will decrease the co-production.

The introduction of SST into service organizations has empowered customers because of the positive outcomes in the service delivery system, such as time and cost saving, speed of delivery, and control over the service delivery (Simon and Usunier 2007; Wang, Harris, and Patterson 2012). Indeed, a customer who engages with an SST to obtain a service by performing a task that previously was done by an internal employee (Meuter et al. 2000) positively affects customers and organizational efficiency in terms of time saving, convenience, and availability (Hilton and Hughes 2013). Consequently, the organization of staff is more efficient because they have more time to do other tasks, benefitting the organization itself and their customers (Eastlick et al. 2012).

SSTs are supposed to bring the service into customers' hands and minimize the service encounter and direct personal interaction. Several articles have pinpointed the importance of reducing the speed of service delivery and waiting time through an SST (Hilton et al. 2013). Indeed, to avoid long waiting times, 505 college students—as part of a scenario-based study—had a higher intention to use SST when ordering in a fast-food chain restaurant (Collier et al. 2015; Simon and Usunier 2007; Wang, Harris, and Patterson 2012).

Autonomy

Autonomy has been used in psychology studies to evaluate a person desire for control and independence in several contexts (Dabholkar 1996). Oyedele and Simpson (2007) in their study have conceptualized autonomy and highlighted independence, mobility, and personal rights as important attributes. They further pointed out that autonomy is built on two dimensions: sensitivity to others' control (SOC) and independent goal attainment (IGA).

From an SST perspective, autonomy—often referred as independence and translated to perceived control (Bieling, Beck, and Brown 2000)—refers to customers that prefer to use a self-service channel over a direct encounter as it affords them to conduct transactions independently with the ability to control and direct the transaction outcome (Dabholkar 1996). Independence has also been used in SST literature in relation to autonomy. From a SST adoption perspective, independence is the amount of control the customer expects to achieve over the process or outcome of a service (Oyedele and Simpson 2007). In other words, users rely on themselves where they are *free* to engage with the SST anytime they see it necessary without going through the customer encounter channel. *Freedom*, is related to the degree to which an SST is used without the needs of assistance (Dabholkar 1996). For example, in a study by Johnson, Bardhi, and Dunn (2008) cited in Ryan and Deci (2000), it has been found that the use of SST in a hotel by tourists and highly motivated by the desire to be more autonomous and independent.

Control

Having control over technology can influence both the intention to use an SST (Oh, Jeong, and Baloglu 2013) as well as customer satisfaction (Collier and Sherrell 2010; Shamdasani, Mukherjee, and Malhotra 2008). From a psychological perspective, control toward SST boosts the self-efficacy of the user, which is strongly connected to the personal capabilities (such as, computer and technology literacy) of an SST user. Self-efficacy has a significant positive effect on the acceptance, usage intention, and perceived value of SST (Johnson, Bardhi, and Dunn 2008; Yen 2005; Zhu et al. 2007).

Once users have control over the SST, they start co-producing the service they need (Dabholkar and Bagozzi 2002; Hsiao and Tang 2015; Van Beuningen et al. 2009). In an illustrative example, Bandura (1997) investigated internet banking users of a major bank in UK and found that the control the customers exhibits over the SST (internet banking) positively impacts the perceived service quality.

Trust

An SST should also maintain a feeling of trust for its users at satisfactory levels. Trust can be defined as a two dimensional construct: 1) trust believe—the user perception of the SST in terms of benevolent, honest, competent, or predictable and 2) trust intention—the willingness of the user to expose himself to the possibility of loss by using the SST (Shamdasani, Mukherjee, and Malhotra 2008). Most quantitative research studies show a significant positive correlation between trust and the use of an SST (Lim et al. 2006) and furthermore, research argues that lack of trust leads to user discomfort and insecurity (Evanschitzky et al. 2015). When an SST such as internet banking, phone banking, or an online purchase system is used, trust is a paramount factor for its use as it directly involves people's finances. In fact, a study, which involved 477 subjects, analyzed several factors affecting the use of an online SST such as online purchasing and concluded that users feel more comfortable in using an SST when trust toward the SST is present (Eastlick et al. 2012; Elliott, Meng, and Hall 2008; Evanschitzky et al. 2015; Liu 2013).

Ease of use

The main driver behind SST implementation is to enable employees to serve themselves during task accomplishment without the need for human assistance (Eastlick, Lotz, and Warrington 2006). To do this, research highlights the importance of a pleasant, easy to use SST design, which requires minimal skills to operate (Dabholkar 1999). Ease of use affects the adoption process of an SST (Bobbitt and Dabholkar 2001; Curran and Meuter 2005; Evanschitzky et al. 2015; Gelbrich and Sattler 2014; Narteh 2015) because the adoption and engagement with an SST requires a customer to use his skills and knowledge in order to operate the platform. Curran and Meuter (2005) have found that customer's engagement with a SST may be constrained by their insufficient knowledge and skills. They may avoid using SST if they expect extra mental or physical efforts Larsson and Bowen (1989). For example, the results of a survey with 771 participants showed that customers use internet banking largely due to its easy to use design and interface (Oghazi et al. 2012). Moreover, users were inclined to depend more on online banking, phone banking, and other related products compared to direct contact with employees unless the interface and the design required a lot of mental effort (Ho and Ko 2008).

Discussion

Drawing on the main findings of SST literature review, in this section, we discuss how the identified attributes contribute to a better understanding of SSBI. Furthermore, we devise a new definition of SSBI and discuss its main components.

Similar to other technologies, especially to SST, ease of use is crucial to SSBI. One of the premises of SSBI is to minimize the operational complexity so that a business user, who typically does not have advanced analytical or technical skills can still use a variety of tools and be involved in data analytics. In other words, users should be able to easily access raw data and transform it into information. To this end, users should engage with relatively easy to use tools and applications. For instance, the "drag and drop" functionalities may enable users to perform certain calculations (which otherwise would require coding) by essentially hiding a complex operation at the back end that end user is not necessarily knowledgeable about.

Likewise, trust is important—given that SSBI supports users to make decisions and take actions by converting data into information. Through the process of data analytics, users should trust the

technologies-in-use, the quality of the data they are accessing and analyzing as well as the appropriateness of the data analytic process. Moreover, it is important to highlight that SSBI should support different levels of users from a technical perspective, which is different user skills ranging from business users to advanced data scientist. They all should express the feeling of trust toward the data available and the information produced from those tools, which makes them more in control as of what tools to use, how to use them, and when in the process of task solving without the interference if IT/BI department personnel.

Furthermore, control is of paramount importance for users to gain independence. Once they feel that they know "how" and "what" they are doing through SSBI, they will feel more in control of the process and consequently less dependent on their IT/BI staff.

In overall, SSBI is more than just a system that provides self-service capabilities. The BI definition clearly states that BI is a set of technologies, tools, and processes that is packaged by the IT/BI department and usually business users only access the pre-defined analytics and reports. Whereas SSBI reflects an approach in which all users are not only surrounded by those technologies and tools but also have the ability to engage with them more independently during their data analytical task accomplishment. Having said that, we propose our new definition of SSBI, which is mainly focused on the levels of co-production and dependency.

> "SSBI is a new approach to BI that aims to increase the level of co-production and decrease the level of individual's dependency during user's engagement with a broad range of applications and tools comprehensively embedded throughout the process of solving an analytical task. "

Co-production from SSBI perspective

An important component of the self-service environment, as seen in our findings, is the co-production (Co-p), which is very frequently referred to it as co-creation (Co-c). Co-p is at the heart of self-service and we consider it as the holy grail of SSBI. It constitutes the actual engagement of users with many resources available throughout the process of solving an analytical task. Those resources are used in coherence with individuals' technical and intellectual skills to access data, structure data, formulate ideas, generate information, and gain insights about a specific task.

The process of co-producing the service is not trivial. It requires a balance among the analytical task at hand, the technological resources available, and users' skills. The more these entities are in balance the more effective is co-production. Simple analytical tasks may require basic technical and analytical skills to access data from one or two data sources; however, more advanced tasks require advanced technical skills to work with many data sources. Indeed, business users and data scientists co-produce on different levels of complexity in an SSBI because of their respective technical skills and job description.

From an SSBI perspective, business users have a higher responsibility. Shifting from information consumers to information authors implies also that responsibilities are shifting from IT/BI departments to other organizational departments. Guided by an SSBI approach, the BI/IT department codifies some of users' knowledge and expertise prior for users to get involved in Co-p.

Drawing parallels with SST, we expect that Co-p will generate similar outcomes, such as time saving, cost reduction, agility in performing data analytical tasks, data divineness, and other benefits for the IT/BI departments. The latter will no longer be overburdened by employees' requests for different reports. Instead, they can focus on SSBI to be in line with the flexible needs of employees, ultimately enhancing their efficiency and effectiveness in terms of better resource allocation, data quality assurance, better management of the SSBI, and improvements to BI platform development.

However, all these outcomes should be treated carefully. Any possible mistake can have serious consequences. For instance, choosing a wrong data set and performing inadequate calculation may lead to wrong results and consequently bad decisions and actions. It can also create confusion and chaos if, for the same issue, different results are presented by different users, such as in a meeting.

Dependency from SSBI perspective

Besides Co-p, another cornerstone at the SSBI approach is the low level of dependency. Through SSBI, users should rely on themselves by feeling free to engage with data anytime they deem it necessary without going through the bureaucracy of requesting the reports from an IT/BI department. To do so, users explore and exploit available data sources to perform data analyses and use it to answer to their questions. In brief, being independent and self-reliant is what drives this process.

In a conventional BI environment, ad-hoc requests are forwarded to the IT/BI department by employees. A considerable time lag can occur until they receive a response, depending on the overload of the IT/BI department, thus making them completely dependent and reliant. On the opposite, SSBI is an approach that weakens the link to IT/BI departments, if not making it absent. In SSBI, users have the needed resources to act independently in accomplishing a data analytical task unless they need advanced expertise.

It is important to highlight that independence has a variable nature, based on the variety of tasks in terms of complexity and extra expertise. For example, a business user might engage in an analytical task where the results are complex and need further refinement or a data scientist might engage in a complex analytical task where an external data sources are needed. In both cases the dependence level changes and IT/BI departments are involved in the process of solving an analytical task.

Conclusion and future research

This article investigates the main SSBI attributes that support the involvement of a business user during knowledge creation. Given the novelty of research on the SSBI area and the similarity of SSBI with SST, we conducted a literature review on SST to meet the aim of the study. We define SSBI as a new approach to BI that increases the level of co-production and decreases the level of individual's dependency during user's engagement with a broad range of applications and tools comprehensively embedded throughout the process of solving an analytical task. This duality of high levels of co-production and low level of dependency are key elements at the core of SSBI.

Based on the findings of this article, we recommend future avenues for IS research. First, future studies should be focused on conducting more empirical studies to understand better on how the SSBI approach generates benefits at both the organizational and individual level. Case studies represents an optimal choice to explore more in depth the practices enacted by an SSBI approach. Second, it is important to understand the way an SSBI develops and to identify the main actors that drive this new approach inside organizations. Third, further research should focus on the process and hidden mechanisms the user follows to solve an analytical task, such as the way data is questioned, analyzed, and developed.

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Notes on contributors

Imad Bani-Hani is a PhD student in Information Systems in the Department of Informatics, School of Economics and Management at Lund University. He holds MSc degrees from Lund University and has extensive experience in the area of business intelligence and software development. His research focuses on business intelligence and analytics with a particular interest in self-service analytics and the mechanisms causing value generation. He has published research in a variety of academic outlets, such as the European Conference on Information Systems and the American Conference in Information System, among others.

Olgerta Tona is an Adjunct Senior Lecturer of Information Systems at the Department of Informatics, School of Economics and Management at Lund University. She holds MSc and Ph.D. degrees from Lund University. Her research focuses on business intelligence with particular interest in mobile business intelligence and big data analytics. Dr. Tona has published her research in such academic outlets as the *Journal of Decision Systems, International Journal*

of Information Management, Electronic Journal Information Systems Evaluation, and the European Conference on Information Systems, among others.

Sven Carlsson is Professor of Informatics at Lund University School of Economics and Management. His current research interests include: The use of ICT/IS to support decision processes, knowledge management, and health information systems. He has a keen interest in the use of critical realism in IS research and design science research in IS. Professor Carlsson has published over 150 peer-reviewed journal articles, book chapters, and conference papers. His work has appeared in a variety of journals including *Journal of Management Information Systems, Decision Sciences, Information Systems Journal, Information & Management, Knowledge Management Research and Practice, Knowledge and Process Management, Journal of Decision Systems, Information Systems and e-Business Management*, and *Computational and Mathematical Organization Theory*, and in such books as the *Handbook on Knowledge Management, Handbook on Decision Support Systems*, and *Design Research in Information Systems: Theory & Practice*. Dr. Carlsson is a regional editor for *Knowledge Management Research and Practice*.

Paper II

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A holistic view of value generation process in a SSBI environment: a service dominant logic perspective

Imad Bani-Hani[a], Jorg Pareigis[b], Olgerta Tona[a] and Sven Carlsson[a]

[a]Informatics, Lund University, Lund, Sweden; [b]Business Administration, Karlstad University, Karlstad, Sweden

ABSTRACT

Self-service business intelligence (SSBI) is an emerging trend in organisations allowing users to become more autonomous in data exploration. Organisations are keen to provide such services for their employees due to its potential benefits. However, there is little empirical knowledge about the process of building a SSBI service and the role of users in this process. From an exploratory single case study of a major Norwegian online marketplace and drawing on service-dominant logic as an analytical framework, we identify and explore two major phases of building a SSBI service: co-production and co-creation. Besides providing a rich description of these phases, this study also explores the way stakeholders are involved and embedded throughout the process of value generation.

Introduction

The nature of today's business demands that business intelligence (BI) extends to an operational level to support a variety of employees during their tasks (Böhringer, Gluchowski, Kurze, & Schieder, 2010) to minimise the risk of no fact-based decisions (Abelló et al., 2013). Often, BI specialists and/or other power users at functional departments are overloaded (Kobielus, Karel, Evelson, & Coit, 2009) by constant requests of reports from different organisational levels (Yu, Lapouchnian, & Deng, 2013). Self-Service Business Intelligence (SSBI) – as a new trend attracting industrial attention – promises to enable executives, managers, analysts and knowledge workers to not only access data, but also to be able to design and build reports based on respective needs (Abelló et al., 2013). In this way, an end-user becomes data producer in addition to the current data consumer profile. However, setting up a SSBI is not trivial and includes many touch points between an IT/BI department and business people, such as during selection of data sources and specifications of data field, data model and semantic layer (Imhoff & White, 2011). In general, the operational level in an organisation encompasses a wide range of employees (such as sales, marketing, operation and customer care). An ineffective design of SSBI (Imhoff & White, 2011), wrong or uneducated SSBI use during data selection and analyses might affect the quality of a business decision.

Given the importance and criticality of SSBI and a lack of knowledge in the BI literature, it is important to have a sound empirical evidence of how SSBI is designed and implemented in practice. Drawing on service-dominant (S-D) logic (Vargo & Lusch, 2017) as a multidisciplinary, dynamic and evolving narrative of value co-creation, this study aims to explore and describe how a SSBI environment is built while considering the inter-relationship between IT staff, SSBI, and users.

Self-service business intelligence in perspective

BI is 'a broad category of applications, technologies and processes for gathering, storing, accessing and analysing data to help business users make better decisions' (Watson, 2009, p. 491). BI addresses also the need for empowering users with access to create their own reports and sharing them with others. SSBI is one BI approach which enables such a capability by allowing various employees at different levels to independently build custom reports and explore previous ones relying to a very low extent on the IT/BI department (Abbasi, Sarker, & Chiang, 2016). Through SSBI the role of an end-user will shift from a simple data consumer to a more consumer–producer one (Bani Hani, Tona, & Carlsson, 2017), which involves processes of co-producing and co-creating with the IT staff; thus permitting users to not only exploit, but also explore data (Stodder, 2015).

Thus, SSBI is:

a new approach to BI that aims to increase the level of co-production and decrease the level of individual's dependency during user's engagement with a broad range of applications and tools comprehensively embedded throughout the process of solving an analytical task. (Bani-Hani, Tona, & Carlsson, 2018, p. 166)

Our adopted definition highlights three key elements vital to SSBI: technology, people and processes. The technology includes the SSBI platforms and tools that support the process of deploying and creating the data models. It is not our goal to explore the varieties of SSBI platforms and tools available in the market, however we put more emphasis on the people and processes involved in the SSBI environment.

Service-dominant logic as an analytical framework

S-D logic has strong connections to IS research. It is depicted as the 'philosophical foundation for service science' (Maglio & Spohrer, 2008, p. 18) and is used for analytical work in several IS studies (see (Lusch & Nambisan, 2015; Yan, Ye, Wang, & Hua, 2010). The changing role of SSBI users, as well as our SSBI definition resonates well with service-dominant logic (Vargo & Lusch, 2004, 2008) as a multidisciplinary, dynamic and evolving narrative of value co-creation through resource integration and service exchange. The central concept of resource integration has been defined as '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, Winklhofer, & Temerak, 2012, p. 2). The notion of customer–producer dyadic has been generalised to actor-to-actor networks (Vargo & Lusch, 2017). As a result, resource integration does not only highlight the active roles of customers and their knowledge and skills, but also those of other actors such as the four categories of SSBI stakeholders (Imhoff and White (2011).

At this point it is important to distinguish between the co-production and value co-creation. From the view point of Vargo and Lusch (2008), co-creation happens when the customer takes the firm's proposed value and integrates it with his or her personal resources to generate value, which is highly subjective to the beneficiary. In contrast, co-production involves the exchange of the operand and operant resources, and develops the proposed value (Sheth & Uslay, 2007). The operand resources are defined as 'resources on which an operation or act is performed to produce an effect' (Vargo & Lusch, 2004; p.2) such as the ATM and online banking platform; whereas the operant resources are the actual human capital that act on the operand resource and are characterised by intangibility such as knowledge and skills (Arnould, Price, & Malshe, 2006; Vargo & Lusch, 2004). Lusch and Nambisan (2015) highlight the role of Information Technology (IT) both as an operand and operant resource. That is, information technology is considered as operand when actors apply their knowledge and skills to produce a service. In similar vain, IT can also be considered an operant resource especially when IT plays an active or triggering role in producing a service (see Lusch and Nambisan (2015). The interactions, resources and potential outcomes that make up the co-production of value propositions are likely to vary according to the social context in which co-production takes place (Edvardsson, Tronvoll, & Gruber, 2011). A further refinement of the distinctions between value co-creation, co-production and value-in-use has recently been offered by Ranjan and Read (2016) who describe co-production and value-in-use as subordinate concepts of value co-creation. This includes sharing of control and knowledge in interaction (co-production) as well as experience, relationships and personalization (value-in-use) (Ranjan and Read (2016). Similarly Hilton, Hughes, Little, and Marandi (2013) remind us that value co-creation can take place even without co-production and considers it as a continuum. Consequently S-D logic should be fruitful to use as an analytical framework in the SSBI context.

Research method

We adopt a single case study methodology as its idiographic nature suits the applied work of our study and empirical account (Hayes, Barlow, & Nelson-Gray, 1999) especially as the area of SSBI is empirically under-explored (Miles & Huberman, 1994; Yin, 2013). The research method employed in this study is qualitative interviews, as we believe that the interview technique will provide rich descriptions (Schultze & Avital, 2011) and insights in understanding how SSBI is built through the collaboration of the IT/ BI and employees.

Empirical site

Our empirical site was a digital marketplace organisation. This organisation has become a central data repository where agencies (private and governmental) constantly send requests in regards to various statistical analysis and ad hoc reports. In addition, high profile sellers are requesting reports from marketing and sales departments concerning their advertisement reach and investment values. Due to the increase in ad hoc requests from different external customers and internal employees in 2010, the management decided to build a more data driven organisational environment where employees could easily access organisational data and work with it to perform their daily tasks more independently.
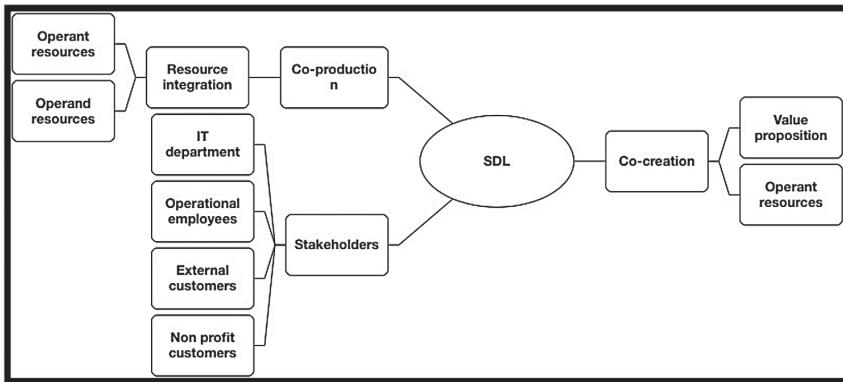
Figure 1. Concepts map.

Data analysis

13 interviews are performed face-to-face and all interviews were recorded (after receiving the consent of the interviewee), transcribed and loaded into NVIVO11. Based on the SDL concepts and their inner elements, a map was created to graphically illustrate the relations and structure of SDL components, such as co-production and co-creation to create the basis for further analysis (see Figure 1). This map is used as an analytical lens to understand the SSBI environment and to develop a holistic view of the value creation process.

Findings

Co-production

During co-production a variety of resources are exchanged among actors in an SSBI environment, categorised as operant and operand resources.

Operant resources – provided by stakeholders to build a SSBI environment – are exchanged among the IT staff and business users during the co-production phase. The IT staff has access to the enterprise data warehouse and other data sources (internal such as price statistics data; and external, such as Facebook and Twitter). To create the required data models, the IT staff should have knowledge about the available data sources; the ETL (extract-transform-load) process and should employ their advanced technical skills during the design and implementation of data models. Data models are developed and maintained through constant updates of data fields and sources and that requires time, technical resources and collaboration with business users. In turn, business users share their business experience, knowledge of industry and operational data to guide the IT staff in creating the most relevant and convenient data models for insight discovery and data exploration. '… You need to have business people articulate what they want to accomplish by using the system that you're going to develop for them.' [Business user].

Operand resources – Through features enabled by an SSBI environment, the IT staff can connect to different types of data sources, conduct data loading and check data consistency during the model development regardless of whether data sources have changed. 'I would

say that we have everything from Excel sheets on shared drives to APIs that pulls data from different sources … the data and the model, the representation to our end users is not going to change.' [Insight department].

Resource exchange – Through resource exchange stakeholders can continuously interact to define and finally deliver mutual valued benefits. In this case, the interaction occurs between the operational business employees and the IT staff to identify the target data-sets and sources.

> The business users or the end users will be included at the beginning of the process and the end by trying to use the data model created then we typically check what dimensions; I mean aggregated data they need and how they need to slice or drill into this data to work with it. [Insight department]

This is an iterative process that includes a series of contacts integrating the expertise among stakeholders to fine-tune the data models provided towards a proposed value of SSBI.

Value proposition – Data models design is a resultant of the continuous effort of stakeholders to exchange operant and operand resources. This creates the ground for the value proposed to users. Business users can now access data, create reports, answer their ad hoc requests, explore new data sources and structure data in a more personalised and autonomous way. 'Self-service business intelligence would allow the people to add new data sources, establish new collection of data, structure them in a simpler, more self-service way' [CXO]. When users become more autonomous in their ad hoc requests, the IT staff is no longer overwhelmed by user requests and can focus more on the strategic and analytical tasks.

Co-creation

During co-creation users engage in the SSBI environment and use the data models that are built during co-production. In co-creation, the proposed value is transformed into value in use where users can acquire the actionable benefits (Vargo & Lusch, 2004, 2008) provided by the SSBI environment. A user – an operant – integrates resources such as business knowledge, technical skills and time with resources imbedded in the self-service platform such as ease-of-use, data models, data source access and export functionalities.

Operant resources – During co-creation users, provided that they have necessary technical skills to be able to work in a self-service platform and utilise its functionalities and services, engage with the self-service platform to carry out a task. 'To do some work; some basic training they might require you to try to understand a little bit of the data and find out what you can get from the queries' [Insight Department]. Some interviewees highlighted the issue of trust. They mentioned that they lacked trust on the data. For this reason, often the IT staff was contacted to provide final confirmation. However, this influences the SSBI environment efficiency (i.e. autonomy and self-service). 'Maybe because of insecurity and maybe I want to double check if the numbers are correct … make sure that the numbers that are popping up in the dashboard are correct, so that's a trust issue.' [Business user].

Resource integration – Users integrate their resources with the available SSBI resources. Users interact with the platform and utilise its functionalities through their technical skills. The SSBI functionalities such as drag-and-drop, visualisation building and aggregation selection are selected and used by users who understand the company business and the report context. Furthermore, through their analytical skills users are enabled to interpret data and

extract insights for their decisions and actions. 'To use SSBI users don't need any advanced skills at all, but in all fairness I think they need to have at least the basic understanding of the company X business model.' [Insight department].

Value in use – as defined earlier, is the evaluation of the service experience during the service consumption. Users can evaluate the service cognitively and identify the value-in-use during their engagement in the SSBI environment. The use of the self-service platform has generated value for several stakeholders inside the organisation affecting departments, employees and even other information systems. At the departmental level, the efficiency of the IT department is enhanced because of the reduced ad hoc queries submitted by employees. Thereby, the IT staff can allocate their resources on more strategic tasks. 'It has definitely reduced the ad hoc queries that we have to answer for rest of the organisations. So, it has freed up capacity for us to be more strategic' [Insight department]. At the individual level, users are impacted financially. By accessing their own data, employees of the sales department can explore data related to their sales activities and create analytics showing the amount of commission they receive each month. 'I used self-service to create reports showing how many sales I got and how much commission I get.' [Business user]. Furthermore, SSBI has influenced their performance on some tasks. By having the freedom to create personalised reports and accessing data freely, users get more autonomous in exploring and exploiting data to answer daily questions related to their work. 'Through the self-service I can build a report to see our users activities on our platform' [Business user]. The value of the self-service platform can also impact another self-service platform through the advanced employment of the data in creating analytics. Advanced users (such as the product development team) can test a hypothesis about user behaviour of a certain functionality built into an information system.

> For instance, we have some hypothesis 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 amount of time I just go into self-service and see if we are getting more people to look at the link by applying this change. [Business user]

Discussion

To minimise the risk of low-quality decisions, this study shows that one should focus on the quality of the SSBI service provided and the competencies needed to operate in a SSBI environment during co-production and co-creation. We have pointed out the different types of people involved with SSBI and through our findings we have highlighted the important elements that they should have to successfully build and operate the SSBI (see Table 1).

From a theoretical perspective, even though S-D logic has been adopted earlier in the IS literature (Lusch & Nambisan, 2015; Yan et al., 2010), to our knowledge, this adoption has so far been limited to studies of co-creational contexts between companies and their customers. In this current study, we provide an empirical account of applying the S-D logic lens in an intra-organisational context stressing the application of the logic in other actor-to-actor networks (Vargo & Lusch, 2017). Our findings support the fundamental notion that co-production is an important step in co-creation of value (Ranjan & Read, 2016) and the healthy interaction between both phases (co-production and co-creation) enable a healthy co-creation of value (see Figure 2). This is reasonable, as the involvement of business users at early stages of co-production will increase the chances of a beneficial proposed value. Given the

Table 1. Summary of findings.

Actors	Co-production		Co-creation	
	Resource Exchange	Value proposition	Resource Integration	Value in use
IT staff	Analytical skills, technical skills	Free-up time for IT staff, centralised data access to users, less ad hoc requests	Technical knowledge, support, analytics validation, data model update	Focus on advanced analytical tasks, self-efficiency of routine requests, prevent abusing the data warehouse
User	Business knowledge, business experience	Autonomy, freedom for exploration, responsiveness, data access	Business knowledge, time, technical skills (low-high), analytical skills, motivation, understanding the firm business model	Data source connection, analytics creation, Effectiveness in customer response, efficiency in task performance, personal gain
SSBI environment	Ability to connect to different data sources, data loading and consistency	Platform for insight discovery	Integrated data model, standard dashboards, data source access, data export, insight sharing	Data model improvement, increase adoption
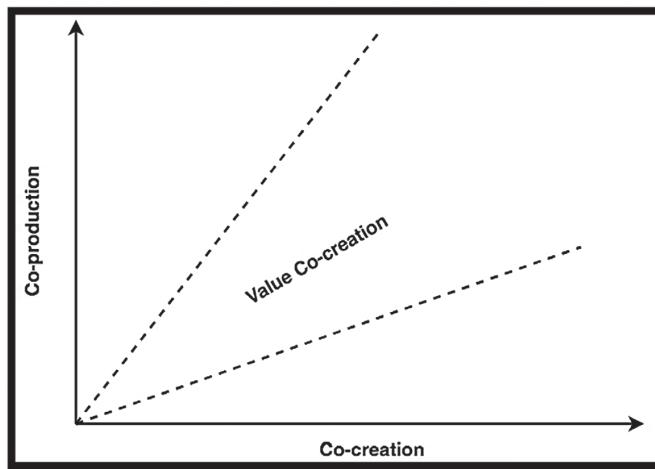
Figure 2. Relation between co-production and co-creation.

service nature of an SSBI environment to provide actionable and operational information needed during daily work, users have to be involved during the design and implementation of data models. This study shows that operant resources are present during the phases of co-production and co-creation. From a firm-customer perspective, the operant resources could be the business employees (the firm resource) or the customer (service beneficiary). However, in a SSBI the operant resource is the service beneficiary and without this configuration the service could have no value, hence no usage. S-D logic argues that co-creation starts when actors engage with the value proposed and co-production is a component of co-creation, which can vary from a total absence to a full engagement (Hilton et al., 2013). This is in contrary to SSBI where co-production is a necessary phase before co-creation happens. This study indicates several implications for organisations. First, companies should invest in a collaborative environment where business users and IT staff/business analysts/data scientists may come together during the co-production phase. Second, companies should invest on necessary trainings that business users might need to feel competent in working in an SSBI environment with analytical tools and reporting applications. Third, companies should assess the value proposed during co-production if that is aligned to the company's objectives that acts as an input during value co-creation.

Conclusion

We have explored through this paper the co-creation of value through the co-production between the users of SSBI and the IT staff by understanding the nature of the process that is taking place when engaging in the SSBI. Reconnecting with the aim of our paper, we have described how SSBI service is built though the essential collaboration between the IT/BI staff and the business users involved. In SSBI co-production is an important step in enabling a healthy co-creation and cannot be underestimated. This study also has pinpointed to the most important elements that influence building the SSBI service as well as its usage by

employees. Based on this research study and empirical account, we have developed an empirically grounded understanding and description of the role of co-production and co-creation in building SSBI service. Future studies may explore the co-creation phase to understand in more detail how users co-create the value and what are the basic skills needed. Due to the fact that not all users possess similar knowledge, skills and motivation to engage in insight discovery and co-creating value, it is important to understand whether there are different modes of engagement that exist and what controls them.

Disclosure statement

No potential conflict of interest was reported by the authors.

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Paper III

Modes of Engagement in SSBA: a Service Dominant Logic Perspective

Completed Research

Imad Bani-Hani
Lund University
Imad.bani-hani@ics.lu.se

Olgerta Tona
Lund University
Olgerta.tona@ics.lu.se

Sven Carlsson
Lund University
Sven.carlsson@ics.lu.se

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.
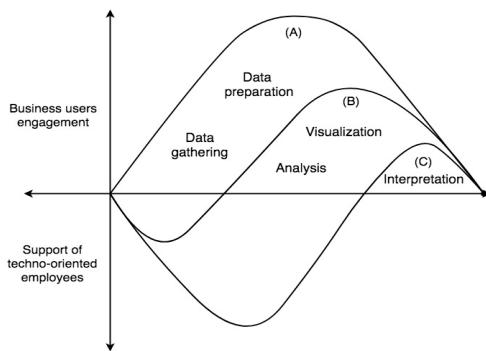
Figure 1: Dynamics in an SSBA

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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Paper IV

Patterns of Resource Integration in the Self-Service Approach to Business Analytics

Imad Bani-Hani
Lund University
imad.bani-hani@ics.lu.se

Olgerta Tona
Lund University
olgerta.tona@ics.lu.se

Sven Carlsson
Lund University
sven.carlsson@ics.lu.se

Abstract

The main premise of Self-Service Business Analytics (SSBA) is to make business employees autonomous during the data analytical process. To empower business employees, organizations are decentralizing their analytical capabilities through an SSBA approach. Yet, little is known about how employees integrate resources, such as, among others, personal competencies, environment resources including technology, and to generate insights in SSBA. Based on the empirical data of a major Norwegian online marketplace and drawing on service-dominant logic as an analytical framework, we identify and explain two types of resource integration in an SSBA environment: direct and clustered resource integration (including 1st tier and 2nd tier) enabled and controlled by three types of institutions. We finally discuss some organizational implications and the meaning of each sub-type of clustered resource integration.

1. Introduction

Business Analytics (BA) entails the use of data in conjunction with several analytical tools and techniques to drive employees and organizations. By definition, it involves "the extensive use of data, statistical and quantitative analysis, explanatory and predictive models, and fact-based management to lead decisions and actions" [1]. Generating value from business analytics tops the agenda of practitioners and academics [2]. For instance, research shows that top-performing organizations use rigorous data analysis to define future strategies and daily operations [3]. Yet, because of organizational structures and employees' capabilities, highly trained and experienced technical employees (often part of an IT/BI department) face a huge overload of continuous analytical reports requested by other departments. On the other hand, given a lack of general business knowledge, technical employees often are forced to solve business problems beyond their capabilities and understanding. To address these concerns, some organizations have started to decentralize analytics by enabling a self-service environment as a way of engaging employees in data analytics with the minimum possible support of technical employees. Self-Service Business Analytics (SSBA) refers to an approach to BA that "aims to give business users access to selection, analysis, and reporting tools without requiring intervention from IT" [4].

In a typical SSBA environment, the technical department provides data, tools and technologies specifically optimized to lower the operational complexity of processing data into information. As a result, the employees become more autonomous in meeting their own information needs, which in turn enables technical department to focus on more strategic tasks [5]. In such scenario, the value of SSBA is co-created between different actors (which in this case are the business and technical employees). Co-creation occurs when employees' competencies (such as knowledge, experience and technical capabilities) are integrated with the environmental resources enabled and maintained by the staff of the technical department. As such, resource integration is a central activity in an SSBA environment to generate value, that is processing data to generate business insights. SSBA Researchers have addressed several aspects ranging from technological design to user acceptance. For example, authors have attempted to describe SSBA architecture to promote more understanding of what SSBA is from a technical perspective [6]. Others have explored the factors influencing SSBA acceptance [7], user uncertainty during engagement [8] and the gap it creates between a user and an IT department [9]. When it comes to the benefit of SSBA, empirical evidence suggests that SSBA enables organizational agility [5] and employees communication and collaboration [10]. However there is still a need to understand how resources integration occurs in an SSBA environment. As such, this paper aims to explain the process of resource integration and its contribution to a successful value generation given the resources available. From a practical contribution point of view (i.e., managers and IT professionals), this paper clarifies the complexity involved in enabling an SSBA environment.

In such depiction of SSBA environment where value is co-created by different actors through the process of resource integration, this

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paper adopts Service Dominant Logic (SDL) as an analytical lens. SDL implies that value co-creation emerges in an interconnected network of resource integration among actors [11, 12].

2. Service dominant logic

SDL is a meta-theoretical framework for explaining value creation among configurations of actors through the exchange of resources [13]. The fundamental notion of SDL is that humans apply their competences (personal resources such as knowledge and skills) to support others and equally benefit from others' applied competences within service-for-service exchange [13]. Lusch and Vargo (13) further define service as a process where one uses personal resources (competences) for the benefits of another entity or the entity itself (Vargo and Lusch 2004). SDL claims that in order to create value, actors engage in an interdependent and reciprocally beneficial resource integration and service exchange [13]. Recently, SDL has shifted towards a more dynamic and system oriented view in which value co-creation is managed through shared institutions (norms, symbols, competence) on a broader scale of resource integration and service exchange process [14]. In short, SDL asserts that value is co-created through 1) actors 2) integrating resources and exchanging services controlled and enabled by the 3) institutions and institution arrangements within the service ecosystem.

2.1. Institutions

Institutions and institutional arrangements are essential during resource integration and service exchange. Institutions encompass actors, norms, rules, beliefs, and general mind-sets that drive actors' actions [15], which are in line with the institutional logic at the individual and organizational level [16]. When actors share the same norms, beliefs, and mind-set, a network effect is created that, in turn, enables a more productive value co-creation [15]. Institutions come in various forms of rules; however Scott (17) has developed a widely accepted categorization built on three main pillars: regulative, normative, and cognitive.

First, the regulative pillar mainly consists of formal rules that enable or constraint actors' behavior in an effort to avoid any kind of formal sanctions. As a result, the actor's behavior is driven to a great extent by self-interest and avoidance of any threatening negative consequences [17].

Second, the normative pillar consists of norms and rules that are defined based on an actor perception of social benefits or constraints.

Those rules are usually formed by the actor as a kind of commitment towards the perceived social expectation and grounded in values of specific industry, groups, and society in general [17]. In short, normative institutions lead to behavior driven by social restrains [18].

Third, the cognitive pillar consists of a set of beliefs originating from actors' perceptions and personal interpretation of their environment [17]. Actors' perceptions and representation of reality as a basis for thinking, feeling and acting lead to a taken-for-granted behavior.

Obviously, the rules, norms, and beliefs originating from the three pillars influence an actor's efforts in accessing, mobilizing, combining, sharing, transforming, integrating resources, and coordinating the resource integration itself [18].

2.2. Actors

First, in SDL, all actors fundamentally integrate resources to co-create value [19]. Consequently, without actor engagement, there is no resource integration and no value co-creation. There is no specific definition of what an actor is, however Lusch and Vargo (13) use a more generic construct related to 'social actors', which can be either interpreted as a single human such as an employee in a organization or a collection of humans making the organization itself. For the purpose of this paper, we identify actors by emphasizing the action, interaction, and engagement with technology required for resource integration and value creation in an SSBA environment. Flowing this line of argument, Storbacka, Brodie (20) conceptualize the actor's engagement with resources as "the disposition of actors to engage and engagement activities as activities to integrate resources facilitated by engagement platforms".

In SSBA environment, there are different types of users that act, interact and engage with a data analytical technology. 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, who have extensive analytical skills compared to those of business users, can analyze 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. Finally, data scientists who have a strong background in mathematics, statistics, and/or computer science, 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 [21]. The focus of an SSBA approach is to empower the first category of users (i.e., business users, such as field and operational staff, sales-people, business developers, and executives/managers). On the other hand, techno-oriented users are employees whose job description is strongly connected to data analytics, programming skills, intimate knowledge about data sources, and semantic meanings.

2.3. Resource integration

Resource integration (RI), a central concept of SDL, 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" [22, p. 2]. However, the notion of customer-producer dyad in this definition is challenged, and it is further generalized to actor-to-actor networks [23] as discussed in the previous section. 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 [24], and second, to encourage innovation through recombination of existing resources [25]. Both reasons require that for a certain activity to generate usefulness, combination or recombination of resources should take place. In that sense, the presence and availability of resources does not imply resource integration per se [13] but rather they can be potential or passive resources. In the same line of thought, once the resourceness (capabilities) of the resource is acted upon or used by an actor's competencies (such as knowledge and skills) it becomes actual resource and its state changes to active [26]. The notion of resource integration in SDL comprehensively takes into account the vast and intrinsic network involved in value creation [23, p.49]. This network is not only a network of resources but also of actors, it is rather a continuous process and connection among all the actors. In an SSBA environment, different resources are available to facilitate and enable user independence in insight generation. Resources such as technology, processes, actors' support (business and techno-oriented users) potentially are the basis for such networks.

Resource integration occurs in the context of a service system in which the actor employs personal competencies, intentions and motivations influenced by the institutions. The actions taken by the actor also influence existing institutions. In other words, institutions influence actors' behavior and vice versa, actors influence institutions through their behaviors.

3. Method

This paper adopts a single case study design [27]. Through qualitative interviews including field visits and secondary data in form of documents, we provide rich descriptions [28] and insights to investigate how resource integration occurs when business users interact 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 requirements: (a) data intensive organization, and (b) an enabled SSBA environment for its employees.

3.1. 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.

3.2. Data collection and Analysis

There are two sources of evidence in this study: semi-structured interviews including field visits and organizational document containing surveys with employees and internal documents such as data sources, tools and techniques for data analysis. Thirteen semi-structured interviews (15 hours were recorded, transcribed, and loaded into NVIVO11 with the consent of the interviewees) took place at Finn.no between February and May 2016, in Oslo, Norway. We have also seized the opportunity to observe and take notes on how the current employees use the SSBA tools.

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 the data source?), service exchange nature (e.g. what do you gain when you engage with data and how does that affect the technical department?) and institutions within the organization (what does it mean 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 and creating the first level of coding (etic) [29]. At the second level of coding (emic) [29] codes were generated incrementally during data analyses [30]. For instance, in resource integration, codes that emerged included: "technical resource", "support" and "personal resources". The coding was done by the first author and confirmed by the second author. Based on the relation between the codes and their corresponding quotation, the findings section was structured based on the following themes: institutions, actors, and resource integration.

The second data source was an internal survey implemented by the technical department with product development departments including product developers, managers, and C-level employees to assess and rate their competencies in 4 processes causing the generation of insights.

4. Findings

The main actors involved during an analytical task, in an SSBA environment, are business users, who engage in daily analytical tasks including business support, and the Techno-Oriented Employees (TOE) who support business employees. Most of the TOE belong to the IT/BI department and other more specialized technical groups, whereas business user work in other departments, such as product development, sales, marketing, and public relations. The secondary data describes the main data analytic processes at Finn.no, namely data gathering, preparation, analysis, and visualization. Furthermore, for each of the processes, Table 1 illustrates the associated competencies of employees.

Table 1: Actor competencies associated with each process.

Process ■Competencies
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 based on pro/cons, …) ■Data source mashup (e.g. combine data sources, Make source selection 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,)
Data 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, confidence interval, stat significance, know A/B, testing boundaries, test=hypothesis,)
Data 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,)

4.1. Enabling Institutions

From an organizational perspective, Finn.no has designed strategies: *"Our organization had just concluded a strategy… the main pillar of that strategy was to become a more data-driven organization." (CFO)*. In this way, the organization aims to develop and influence the normative institutions by requiring not only a real strategic management support but also perceiving the readiness of employees and supporting the early adopters of this vision.

Interestingly, before introducing the new strategy, employees were involved in some informal data analytics to be independent from the IT/BI department and efficiently fulfill their own daily needs driven by a data-driven self-interest as a way of reducing the risk of miss-informed decisions. *"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)*. Those small pockets of employees (groups within the department), as described in the previous quote, are basically the result of the employees' awareness about the importance of data in decision-making and backing up any claims with facts. *"we make*

business decisions based on the data we have available and if some claims are not true we try to gather what's necessary [data] to get the facts and back up what you say? (business user).

Obviously, regulative institutions had an important role to play when those small groups were created. This is a good example when organization falls behind in promoting a strategy or vision; the actual need of employees precedes organizational actions. Consequently, the organization took many initiatives to support such movement by including 'data-driven' as a main pillar in the organization vision. The management also started to provide a more self-service and data driven environment by introducing dynamic data metrics of the organization activities visualized on big screens in most of the departments as observed at Finn premise. The have also democratized data through the organization by providing access to existing data model already developed by employees and build new ones.

In other words Finn realized that they should 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…"(TOE)*

In an effort to make data a part of everyday decisions through the organization, the management has created initiatives such as awareness seminar, trainings, and success stories related to the data driven mind-set. They have also mentioned that they need to have data embedded in any decisions they make and be part of their daily routines by metaphorically referring to the use of data as 'instinct'. *"What we essentially said in our organization is that we want data to be a part of our instinct." (CFO)*, *"Our organization strategy has six areas, one of the six areas; data in our spine. It was one of the focus areas and we some activities [seminars and workshops] related to that." (business users).*

Some employees perceive these transformations in the organization as 'core changes' that enable them to work independently with data. The initiatives from the organizational management have affected their cognitive institutions such as the perceptions and representation of the surrounding reality. *"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" (business user), "making kind of the best decision possible and try really to be data driven and challenge others being data driven at my unit and also we work a lot cross-rational so trying to get them to be fact-based and data driven, but it's kind of a transformation I would*

say." (business users), "I would say it's like we have this special culture. It's kind of a bit intangible I would say, but it's like how I should say this… is related to our standardized processes" (business users).

4.2. Actors

Based on our finding, four types of actors are identified. First, *business user* are the actors who initiate the process of data analytics to either address a problem/opportunity or answer a question. Second, *business support* are those actors who provide support for the business user in case they need an advice regarding a business situation. Third, *1st tier TOE* are the actors who provide technical support for business users and considered the first point of interaction with the technical department. Fourth, *2nd tier TOE* are the actors who support 1st tier of TOE in case a support could not be provided by the latter.

4.3. Resource integration

From a SDL perspective, operant and operand are recognized as two types of resources in a service system. The operand resources are defined as "resources on which an operation or act is performed to produce an effect" [31, p.2] (e.g., tools and data analytics platform), whereas the operant resources are the actual human capital that acts on the operand resources and are characterized by intangibility (e.g., knowledge and skills [31, 32].

Based on the SDL resource categorization, in an SSBA environment we identity three main categories of resources that are exchanged during resource integration: (1) Environment Resources (ER), such as tools and applications that support data access, manipulation and processing, documents and many others (operand resources), (2) an actor's Personal Competencies denoted as (PC), such as technical skills, business knowledge, and experience (operant resources); and (3) other actors' personal competencies when support is needed denoted as Other Personal Competencies (OPC) (operant resource). These resources are enacted through two main resource integration patterns, which is direct and clustered resource integration.

4.3.1. Direct Resource Integration

In direct resource integration, *a single actor* enacts appropriate resources to generate insights. In this type of integration, a business employee has the capability to independently engage in the data collection process, data preparation, data analysis, data representation (visualizations), and interpretation of the results to generate insights (i.e., without the support of TOE). This process is realised by recalling the actor's competencies,

such as business knowledge and relevant technical skills (see **Table 1** capabilities) to engage mainly with ER available in the SSBA environment. Often a business user engages through the whole processes of data analyses to generate insights by interacting with ER only. A business user stated: *"I organize my sales data in a specific format [PC, ER] to see if I am missing commission" (business user), "I sit and play with data [ER] and looking for some answers to solve questions and when I think have sort of found something I usually share it with one of the guys sitting next to me"(business user)*

In such case it is clear that the user possess the required competencies to assume independence and interact with several environment resources such as data models, analytical tools and business segmentation.*"I use Tableau [ER] and build reports based on customer data [ER] and business segments [ER] to show me how many impressions [i.e., views] per search on our platform…" (business user),* *"I use self-service tools [ER] to see how many save ads and how many have saved searches on this topic." (business user).* In certain cases the task at hand may be complex and to assume independence business users should own somehow advanced personal competences such as data manipulation, data integration and statistical analysis (please refer to Table 1) to design specific reports in specific formats. *"I have good technical experience [PC] in Tableau [ER] so I have created some customer reports based on my business understanding [PC] [and placed them] on my desktop using the desktop version of Tableau [ER] … I can easily extract very quickly all the data on my machine and all the tables and formatting the way I want." (business user)*

The availability or resources and access to data are important but not enough to assume independence. A user should have the ability to orchestrate tools, data, and analytical processes in line with the personal competences (see Table 1 for detailed needed competencies) to answer either a problem or an opportunity. *"So I need to go and make an extract from Tableau [ER] and an extract from CRM [ER] system and then match that data to get the industry and size of the company [PC] … so I pull data from different sources and put them into Excel [ER] … 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 [ER] and then I sometimes use [PC] different tools [ER] to scrape website [data] in order to get data structures of competitors… I use Google Analytics as well. [ER]" (business user)*

4.3.2. Clustered Resource Integration

In the clustered Resource integration, *a network of actors* enacts appropriate resources to generate insights. Due to lack of necessary business knowledge or skills to perform a task, a business user may require some assistance from 1st tier TOE (i.e., enact other personal competences) to complete a task. They may also need assistance from business support employees to understand a certain business situation, which again requires enacting other personal competences. Furthermore, a network of actors collaborating together and enacting ER is noticeable. The more OPCs are enacted, the bigger the network becomes.

- **1st-tier**

The 1st tier is a resource integration pattern where only one cluster is created before developing the desired insight. Despite the enactment of OPC (technical or business), the initial actors still lead and control the insight generation. In other words, business employees deliver the final results after they have enacted PCs, ERs, and OPCs to perform a task. In contrast to the previous resource integration type — where support is not needed—, business employees are not independent.

Concerning the nature of support and assistance of 1st tier TOE provide. *"One would be just getting help extracting or manipulating [OPC] the data or just getting the tie (connection) to do it." (business user),"I personally want to include them more and not just extracting the data and putting it up on the dashboard." (business user), "Sometimes 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 [OPC] to get some data directly from the data base and provide me an answer to my questions."(business user)*

The need for technical assistance is mainly caused by a lack of PC such as the competencies needed to identify data sources and assess the quality of data and many other related to data gathering (see Table 1).*"There are tremendous amount of data base connections that have similar names that I don't understand [PC] 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,"but if it's more advanced I go downstairs [to the IT/BI department], scratch on the door and ask for help."(business user)*

Furthermore, a lack of knowledge on how to prepare data once a data source is identified and the uses of several data sources also drive business users to ask for support. Table 1 shows the different activities related to data preparation. Some of them are less complex and some need

special skills. *"Its tough for me to create a whole new report because I don't really know [PC] what data have good quality and clean. I mean what data sources have good and useful data and which one have dummy data"*, *"I include them [techno-oriented employees] Not just relieving [setting up] the dashboard or the data, but also including them in problem solving. "(business user)*

Users also require assistance in less complicated tasks either to confirm what they did or ask about a specific issue they have. *"…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" (1st tier TOE)* *"if I do more complex analysis; I try to go back and ask them what's wrong with what I have done so that they could pin point or try to look at my stuff and see if I have done anything that doesn't make sense" (business user)*

The variability of the employee's business experience and knowledge requires business support to be available especially in complex situations. Formulating a problem and developing a question involves a deep and valid understanding of the information gathered in connection to the business involved. *"I think it's also to get the understanding of it's more than just insights; what's happening on the business side, what's happening on the competitive side like getting more the holistic perspective of the market place?" (business user)*, *"Are there any products that we sell to our current people and the pricing manager in my department and there I really challenge him to kind of understand what's going on there and use that data" (business user)*, *"we try to work together as a team and solve these tasks together and we also have other departments that we can involve. We have…" (business user).*

- **2nd-tier**

The 2nd tier is a resource integration pattern where more than one cluster is created before developing the desired insight. In some cases, the data available for a business employee is not complete and new data is required. In that case, the business employee contacts the 1st tier techno-oriented employee. If the data is available in the data warehouse then they contact a more specialized within the department (2nd tier TOE) to load it into the data model and make it available for others. *"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 [ER]. So, if it is not, then we take over the report development,* consult other departments and then we provide the answers directly." (1st tier TOE).

However, if the data is not available in the data warehouse, the 1st tier techno-oriented employees contact more specialized employees from other technical department. *"…the first step in for instance, in getting a new field into the self-service [ER] tool that would be to have a change ticket with the data warehousing team [OPC] right. So the data warehousing team would then transfer data from any source system and then amend it to a table depending on if it's a dimensional or fact that would fit into all pre built model. So as soon as they've made that field available within the data warehouse either me or X can go in and update [PC] our the self-service [OPC] data model" (1st TOE).*

5. Discussion

SSBA is an approach to data analytics that basically enables its users to experience a higher degree of independence while exploring and exploiting data in the process of attending to a business need [5, 33]. Yet, this process depends on institutions, resources, and actors that are active in a SSBA environment. The findings of this study, in terms of insight generation, are in line with SDL in that the network structure of the interplay between actors and resources is enabled and controlled by institutions to co-create value [14, 34]. The focus of this study is on resource integration shaped by institutions in an SSBA environment once the process of insight generation is initiated.

During resource integration, different actors collaborate together to co-create the desired value. Solving an analytical task often requires a business user to collaborate with others (i.e., as per their corresponding job descriptions). Because institutions shape actors behavior (and vice versa) [18], they are also expected to coordinate resource integration during a collaborative work. This is in particular important when conflicts emerge as a result of individuals or organizations who act according to their self-interest [35]. In this context the cluster become a silo of resource integrating through collaboration and cooperation. Once this cluster is institutionalized, it becomes a source for insight generation, hence delivering the premise of SSBA.

While institutions describe and conceptualize user behavior in an SSBA environment, resource integration depicts the actual engagement of an actor with the resources available by enacting and interacting with data, technology, other actors and resources to address a business need. Based on our findings, two types of resource integration occur, namely the direct and the

clustered resources integration. In the direct resource integration, the enactment of resources occurs in a linear fashion. A business employee recalls PC to interact with ER1, ER2 … ERn until data insight is generated (see **Figure 1**A). There are no specific rules on what and when certain resources are enacted because it mainly depends on an employee's PC and how institutions affect his behavior. It implies that collaboration is absent in this case and the only coordinating institutions are those belonging to the actor and established within the organization. By linear we mean that no OPCs are enacted in such interaction and the driver is only one actor and own PC, which prevent the formation of a cluster, as we see next in the clustered resource integration. This scenario does not imply the absence of value co-creation. In fact, the SSBA environment in which this scenario and the next one occurs is fully maintained and managed by techno-oriented actors.

In the clustered resource integration, due to the fact that actor's PC entails technical skills, experience, and business knowledge, the probability of requiring assistance in certain tasks cannot be neglected. In such case, the enactment of resources does not follow a linear fashion but a rather nested one. For example, a business employee enacts PC to interact with ER1 then ER2 and then maybe followed by OPC1 then OPC2 … OPCn, ERn..There is no

specific path whether ER or OPC comes first, however every time an OPC is enacted a cluster is created. The reason for the emergence of such cluster is that each OPC represents the competencies of other employees in an SSBA environment or what we refer to as support actors. Those actors in their turn can enact ER to provide assistance, hence creating a cluster (see **Figure 1**B). Based on our findings, two types of cluster can emerge, that are 1st tier cluster and 2nd tier cluster. In both types of clusters, institutions are important as they safe guard the resource integrations process during collaboration. The 1st tier cluster constitutes the direct support that a business user provides in case the initial actor lacks specific business understanding or the techno-oriented user provides support in answering a technical question. In both cases, support is provided directly without the need to include more specialized people. This scenario is a direct result of miss alignment between an actor's PC and ER during resource integration. The 2nd tier cluster (see **Figure 1**C), emerges when 1st tier cluster cannot provide the needed support and more specialized people are recruited. In such scenario, the support actor in the 1st tier cluster creates a cluster on his own. Both scenarios are an empirical proof of the network nature of resource integration described in the process of value co-creation described by SDL [15, 36].
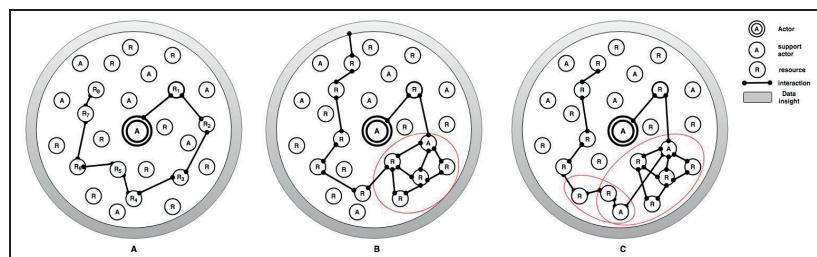

Figure 1: Patterns of resource integration

From an organizational perspective, in direct resource integration, employees' work efficiency is enhanced primarily because they will feel in control of their work and secondly, the time it takes to communicate with other employees will be significantly reduced. Moreover, data analytics decentralization [37] can be achieved because there will be more autonomous users and fact-based decisions may be infused across levels of an organization [38, 39]. Furthermore, direct resource integration aids in curtailing the time needed for supporting actors like techno-oriented employees to handle daily ad-hoc data analytical requests, in line with other recent research that indicates that IT/BI

resources should be used more efficiently and effectively on strategic projects [40, 41].

In term of clustered resource integration, we have described two types of clusters, namely 1st tier and 2nd tier. In the 1st tier, business users competencies are not fully aligned with the resources available, mainly because of the lack of certain skills (business of technical) and capabilities, which pushes them to require support (business or technical). However, both cases institutions coordinate the process of data analytics especially when several actors are involved and collaboration is a must. In that case organizations can act by offering training programs for employees to obtain more solid

technical knowledge and enhance their competencies. Second, organizations can also 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 and abilities on completing an analytical task. In the 2nd tier, more specialized support is needed due to the fact that certain resources are missing or ill configured in the SSBA environment which limits its potential value. As such this type of clusters affect directly the SSBA environment and unveil hidden issues that may affect many business users.

Table 2: Summary of resource integration patterns

Resource integration pattern	Description – SDL view	Implication - meaning
0-tier (direct)	The actor's institution, personal competencies (knowledge and skills) and SSBA environment (technology and data provided) are aligned and enable a self-governing value co-creation.	The ideal scenario where the user competencies are fully aligned with the SSBA environment resources, which results in full autonomy and independence.
1-tier (1 cluster)	The actor's institution or personal competencies (knowledge and skills) fall behind leading to the creation of a network.	There is a miss-alignment between the users competencies and the other resources provided in the SSBA environment. Organizations should provide training sessions and mentorship programs.
2-tier (2 clusters)	The SSBA environment lacks certain resources and requires improvements. It prevents actor from successfully integrating resources.	The SSBA environment is still immature and prevents users from having a successful insight generation. Organization could re-evaluate the SSBA environment and unveil potential issues.

Our research contributions need to be considered in light of this study's limitations. First, this study does not explore the process of how the interaction between the different elements of an SSBA environment occurs (actor-resource, resource-resource, resource-actor and actor-actor), but rather uses as grounds to study the arrangement of ER, PC and OPC when integrating resources in an SSBA environment. Still, we believe that this is an opportunity for some new avenue of research in order to better understand the mechanisms that may exist during the process of resource integration. Second, future studies could also investigate a SSBA from a decision-making perspective as a final outcome of the data analytics process. Finally, It would be also interesting to investigate the role of sense making while interacting with the SSBA environment resources.

6. Conclusion

This paper investigate resources integration patterns in a self-service approach to data analytics enabled by the SSBA environment through the lens of SDL [13]. By portraying SSBA environment as a service environment within an organization, we have discussed how SSBA environment nurture regulative, normative and cognitive institutions. We have also identified two major types of resource integration and described their patters in such environment. Finally, we describe each pattern in relation to SDL and its meaning from an organizational perspective.

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Paper V

Summer 2017

Enabling Organizational Agility Through Self-Service Business Intelligence: the case of a digital marketplace

Imad Bani Hani
Lund University Sweden, imad.bani-hani@ics.lu.se

Sinan Deniz
Lund University Sweden, sinan.deniz@ics.lu.se

Sven Carlsson
Informatics, Lund University School of Economics and Management, sven.carlsson@ics.lu.se

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Imad Bani-Hani
Lund University
Sweden
imad.bani-hani@ics.lu.se

Sinan Deniz
Lund University
Sweden
sinan.deniz@ics.lu.se

Sven Carlsson
Lund University
Sweden
sven.carlsson@ics.lu.se

Abstract

Many organizations have adopted business intelligence and analytics systems in order to cope with the increasing digitalization of data intensive environments. In this paper, we study the role of self-service business intelligence (SSBI), a certain capability provided by a business intelligence system, in enabling organizational agility. In particular, the research question we address is as follows: How does self-service business intelligence enable organizational agility in a multi-sided platform? We focus on two types of organizational agility – namely, market capitalizing agility and operational adjustment agility – and identify how SSBI enables these capabilities in a multi-sided platform environment. We conducted 12 qualitative interviews focusing on Norway's biggest digital marketplace, Finn.no. Our results indicate that SSBI plays an important role in enabling 1) market capitalizing agility by providing a better understanding of supply and demand participants, more access to traffic data and user clickstreams, fast response to requests, and increased access to supply and demand navigation behavior and 2) operational adjustment agility by redefining current organizational structures, empowering employees, providing equal access to organizational level data and opportunities for data manipulation. The findings provide empirical evidence for the role of SSBI in enabling organizational agility within the context of a multi-sided platform environment.

Introduction

The increasing digitalization of previously non-digital goods and services has created an important social, organizational, and economic phenomenon during the past decade (Yoo et al. 2010). During that time, information and communication technologies (ICT) have contributed to the productivity and efficiency of service firms opening new markets and promoting new kind of services (Brynjolfsson and McAfee 2014). Furthermore, combining ICT with knowledge and skills allows information to be repackaged and transferred leading to new opportunities for service exchange and combinatorial innovation (Vargo et al. 2015).

A digital marketplace is an illustrative example of how service exchange is facilitated through information repackaging and innovation. A digital marketplace is an ecosystem of several participants interacting together for shared benefit (Rysman 2009). Parties such as buyers, sellers and market intermediaries (Bakos 1998) use a digital platform and a service provided by the digital marketplace. This results in an abundant amount of data in the form of clickstreams and data logs. Such data sources contain hidden information that could be leveraged to optimize the digital platform and provide insight into user needs and behaviors, hence coping with the changing nature of the service provided. An example of such leverage would be to uncover users' browsing and purchasing behaviors and patterns (Chen et al. 2012) – various analytical tools can be used to create a trail of the users' online activities – to deliver a more customized and personalized service with the help of users' clickstream analysis.

Such data-intensive environments are characterized by rapid and uncertain changes that constitute the foundation for an innovation-driven economy (El Sawy et al. 2010). One concept that has been developed to respond to data-intensive environments is *organizational agility* (Singh et al. 2013). It is the capacity of an organization to efficiently and effectively allocate its resources to value creation and capturing activities in response to various internal and external conditions (Teece et al. 2016). Past research on the concept of agility stresses the importance of managing demand and supply side uncertainties (Stigler 1939; Teece et al. 2016) while making the necessary organizational changes (Worley et al. 2014). When it comes to the relationship between IT and organization agility though, past research has identified the role of IT both as an enabler (Böhringer et al. 2010; Sambamurthy et al. 2003) and a constraint (Böhringer et al. 2010; Overby et al. 2006) on the path to organizational agility. Because of this non one-size-fits all relationship between IT and organizational agility, making organizations agile can be fairly challenging and costly due to different business models, organizational structures, IT systems, and investments to support the IT-organizational agility relationship. Therefore, it might be argued that the role that IT plays in supporting organizational agility is context sensitive (Teece et al. 2016).

Industries have widely adopted business intelligence and analytics solutions to gather and analyze data (Chaudhuri et al. 2011). Business intelligence (BI) refers to the various methods and processes used to turn data into information and then knowledge (Lönnqvist and Pirttimäki 2006). As we have noted above, this knowledge could be in the form of purchase behavior and clickstream analysis. BI has also evolved since it was introduced in terms of its capabilities. Mobile, collaborative, and self-service BI are considered BI capabilities as they enhance various BI features such as mobility, access and collaboration.

For example, BI systems have included mobile access to the main BI infrastructure in response to the advancements of mobile computing (Tona and Carlsson 2013). Also, such systems have addressed the need for empowering users with self-service BI (SSBI) to access and create their own reports and share them with others. These capabilities play an important role in enhancing organizational agility in response to a rapidly changing business environment (Chen and Siau 2011).

Even though there is an increasing practitioner interest in SSBI, past literature emphasizing the role of SSBI in empirical settings, especially in a data intensive empirical context, is lacking. To address this issue, this study investigates the following research question; *how does self-service business intelligence enable organizational agility in a multi-sided platform environment?*

We answer this question by conducting 12 qualitative interviews focusing on Norway's biggest digital marketplace[1], Finn.no. We identify two important findings. First, SSBI contributes to organizational agility by allowing the organization to capitalize on the market while meeting the different needs of

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[1] In terms of overall traffic and number of listings: http://www.schibsted.com/en/Press-Room/News-archive/20172/Record-Traffic-in-2016-for-Finnno/

customers. Second, SSBI contributes to organizational agility by helping to adjust the operational issues of the organization. Thus, this research provides theoretical contributions in terms of the role SSBI plays in data-intensive organizational environments, such as a digital marketplace, through its impact on organizational agility. From a managerial perspective, this study provides insight into the main points that are important in enabling organizational agility through SSBI. Thus, managers can support certain areas if they need to be more agile externally (market capitalizing) or internally (operational adjustment).

Organizational Agility and SSBI

Organizational agility is the capability of a company to address challenges that can occur from inner or outer environments for the sake of moving with flexibility and speed relative to its competitors (Sambamurthy et al. 2003; Singh et al. 2013). Rather than being ad hoc and unsystematic, organizational agility is conceptualized as systematic variations in organizational outputs, structures, processes, and actions that are executed consciously to gain competitive advantage (Sanchez 1995; Tallon and Pinsonneault 2011).

Many products and services are embedded with digital technologies in which they operate as digital platforms in enabling new forms of business models (Bharadwaj et al. 2013). One of these business models is a multi-sided platform where many different stakeholders are brought together via their interactions through the existence of a digital platform to conduct commercial activity, i.e. a digital marketplace (Evans and Schmalensee 2016). In this context, the main concern of the platform owner is to figure out how to implement various incentives in the marketplace so that participants can interact with each other given that the value creation is contingent upon this (Anderson Jr et al. 2013). Furthermore, digital marketplaces are usually "situated within the broader ecosystems of firms, governments, regulation, and other institutions" (Evans and Schmalensee 2016) in which the owner of the digital marketplace needs to comply with laws and regulations coming from these bodies and reflect these changes in its platform when needed.

Moreover, in an era where competitive advantage is fleeting (D'Aveni et al. 2010), any given organization needs to move faster relative to its competitors and have the capacity to be flexible for the sake of effectively changing and adapting to new purposes and responding to emerging possibilities (Agarwal and Tiwana 2015), therefore having the capability of organizational agility (Lu and Ramamurthy 2011). Such a capability can show two different dimensions: *market capitalizing agility* and *operational adjustment agility* (Lu and Ramamurthy 2011). Market capitalizing agility refers to a firm's ability to constantly look for areas to improve upon in their offered product or service and leverage on these to meet ever-changing customer needs. Operational adjustment agility, on the other hand, refers to a firm's ability to address their inner workings – distributed responsibility, data ownership and transparency across organizational units, etc. – as a foundation for responding to outer changes.

In order to achieve such firm-wide capability, organizations need leverage on the processing of large volumes and distribute up-to-date information with the help of various IT-enabled systems (Volberda 1997) in which IT acts as the foundational building block of the digital platform that supports the digital marketplace (Sambamurthy et al. 2003).

Business intelligence (BI) symbolizes one of the most popular types of decision support systems (DSS) (Arnott and Pervan 2014) mainly because it is employed in a wide range of industries such as retail, telecommunications, healthcare, transportation and financial services (Chaudhuri et al. 2011). Even though there is not a widely established and recognized definition of BI, in this paper we adopt the following definition: *"a broad category of applications, technologies and processes for gathering, storing, accessing and analysing data to help business users make better decisions"* (Watson 2009, p. 491).

Business intelligence systems have experienced fundamental changes in terms of data structure and its system reachability. This is mainly due to the introduction of social media, mobile devices and machine sensors data having different volumes and rates of growth (McAfee et al. 2012). Also, the scope of BI is no longer limited to a strategic level but extends to an operational level reaching more employees in the organization (Böhringer et al. 2010). From a decision environment perspective, BI systems can support flexibility and risk (Işık et al. 2013). By employing BI at managerial and operational levels, value in both business processes and organizational performance can be generated (Elbashir et al. 2008).

Changes in decision-making needs are expected in today's organizations due to exposure to high velocity data, hence requiring a certain amount of flexibility from the systems supporting the human decision making (Beynon et al. 2002). BI has evolved in this context by continuously involving technologies to cope with industrial changes, such as introducing Hadoop clusters in their infrastructure (Phillips-Wren and Hoskisson 2015) and enabling users to access the BI system through mobile devices such as phones and tablet PCs (Tona and Carlsson 2013).

BI has also addressed the need for empowering users by allowing them to create their own reports and share them with others. Such empowerment is delivered by a particular capability of a BI, SSBI, which enhances certain BI characteristics such as reachability and access. Such analytical capability turns out to be a critical asset in making an organization more agile in its response to changing business needs and dynamics (Yoo et al. 2010).

Authors such as Knabke and Olbrich (2013) have studied the agility aspect of business intelligence. In their study they identified eight aspects that enable an agile business intelligence solution and built a framework of agile properties with the ultimate aim of providing a common understanding of BI agility. Those aspects and properties are in line with the characteristics of SSBI as they more or less focus on the timely response (Galliers 2006) of BI users to analytics demands, and the change of current user behavior (Dove 2005; Galliers 2006) as they start using the data to exploit and explore. Another important aspect is the changes in the business process where SSBI enables users to be more autonomous in processing information and therefore their actions. Reusability, configurability and scalability are the three basic principles identified by Dove (2005) which are also supported by SSBI as the user re-uses, reconfigures and expands analytics they previously created independently of the IT/BI department.

Method

The research method adopted in the paper is qualitative interviews, as we believe that the interview technique will provide rich descriptions (Schultze and Avital 2011) and insights into understanding the role of SSBI in the organizational process and business. To do so, it was important to have a good understanding of how SSBI is used in different departments of an organization in terms of its role, usage and business process facilitation, which we believe is aligned with the strength of qualitative studies.

Empirical Account

The empirical data was collected at Finn.no, the top digital marketplace in Norway. Finn.no was founded in 1996 focusing on classified advertisements but with a great vision. Today, Finn.no is not only a digital marketplace where buyers and sellers use the company's digital platform to find a common ground to perform transactions, but it has also expanded its service offerings to include: providing statistics about real estate, monetary statistics on vacation rentals, statistics about population clusters and concentration in specific areas and to include different parties such as governments, newspapers, students and research labs.

Finn.no has become a central data repository to where agencies (private and governmental) constantly send requests regarding various statistical analyses and ad-hoc reports. In addition, high profile sellers request reports from marketing and sales departments with regards to their advertisement reach and investment values. Due to the increase in the number of stakeholders and growing digitalization, in 2010 Finn.no's management decided to build a more agile and data-driven organization where employees could easily access any organizational data and use it to perform their daily tasks more independently and with more agility.

For that purpose, a self-service business intelligence solution has been adopted with the aim of augmenting employees' capability and agility in answering requests from external customers together with fulfilling their own needs in terms of report creation, making Finn.no an ideal subject for our investigation.

Due to the exploratory nature of this study, participants holding different positions were selected from several departments resulting in twelve interviews (see **Table 1**) held at Finn.no. The interviewees were selected based on the snowball sampling strategy (Biernacki and Waldorf 1981) as each interviewee pointed out other potential subjects explicitly or implicitly through drawing "mock-ups" explaining their use of SSBI to communicate with different employees (**Figure 1**).

The mock-up drawings brought more description and even encouraged the interviewee to be more engaged during the interview by providing more information of the role of SSBI in their daily work.

Interviewee	Duration (min)	Department	Position
A	40	Insight	Senior insight interpreter
A	180	Insight	Senior insight interpreter
B	60	Sales	Market researcher
C	30	Sales	Market researcher
D	60	Insight	Senior Analyst
E	30	Marketing	Public relation and communication advisor
F	50	Product	Business developer
G	105	Product	Business developer
H	45	Sales	Market advisor
I	60	Management	CFO
J	105	Sales/Way of sales	Sales project manager and consultant
A	70	Insight	Senior insight interpreter

*Table 1: Interview duration and target departments*
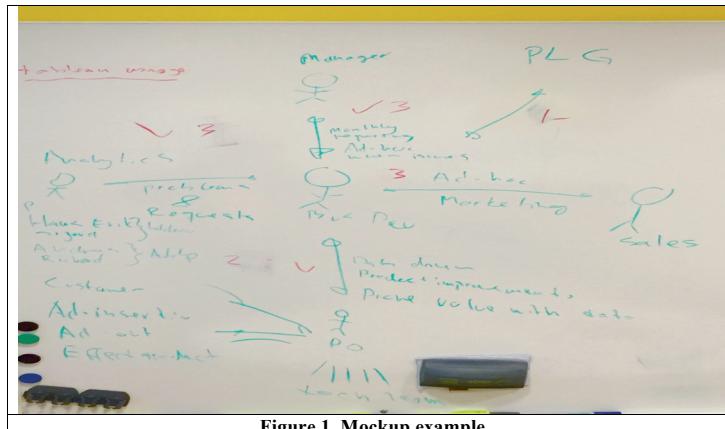
Figure 1. Mockup example

Data Analysis

The data analysis started during the interviews. It was important to take notes in relation to the discussion with the interviewee. These notes were cross-validated with the interview transcriptions which resulted in a preliminary scanning of the interview contents. Nvivo10 was the main data analysis tool used in our process.

This study employed two levels of coding schema, *etic* and *emic,* introduced by Miles and Huberman (Miles and Huberman 1994). The first level of coding (etic) was build upon our conceptual framework presented in section two. These codes were more general in nature as they reflected general concepts of business agility adopted from (Lu and Ramamurthy 2011). The second level of coding (emic) was more iterative in nature and nested inside each general code [42]. In the second level of coding, each author developed codes separately and then cross-validated it with the other (**Table 2**). The iterations further decomposed the general codes targeting a more specific role that SSBI plays in enabling business agility, as discussed in the next chapter.

Table 2: Data analysis example				
Interview Quote	Theoretical concept (etic)	Second level code (emic)		
		Author 1	Author 2	Final
'So I use self-service for analysis to see how many users save ads, how many have saved searches on this topic for instance'	Market capitalizing agility	Increase knowledge on customer needs	More understanding of platform users	Better understanding of supply and demand

Findings

The main goal of a digital marketplace is to act as a matchmaker between the seller and the buyer through a digital platform that facilitates this process. Due to the nature of this business being characterized by data intensity, technology plays a central role supporting the organization's activities between different departments as a whole and employees per se to support agility.

Based on our conceptual framework and the analysis of the data collected, we have identified several factors that play a distinctive role in enabling business agility such as (1) employee empowerment, (2) relationship with the core unit, (3) supply and demand needs, (4) response time to customer requests, (5) digital platform data, (6) user data, (7) data access and (8) data usage. Those factors have been clustered based on our theoretical framework.

Market Capitalizing Agility

Better Understanding of Supply and Demand.

The fundamental unit of analysis in a digital marketplace is the interaction among platform participants (Van Alstyne et al. 2016). In other words, it is crucial for the platform organization to understand the needs of platform participants and create the needed mechanisms to match them as effectively as possible. With this factor in mind, SSBI enables organization-wide access to both supply side and demand side data in order to identify the particular needs of these parties. A business developer mentioned:

"So I use self-service for analysis to see how many users save ads, how many have saved searches on this topic for instance"

Such organization-wide access to the data gives organizational units an ability to specialize and have an autonomous structure in regards to understanding the particular needs of each customer segment. For example, an employee from a product department states:

"Then I go and check self-service and see how many views a particular customer has averaged per ad so far and I compare it with competitors to see if this is good or bad and how many views customers have per money spent. I do that kind of analysis using self-service and its very ad hoc."

Such ability gives detailed insights about particular customers and helps target each of them individually. For example, if a supply side participant intends to sell his/her house and to get as much detailed information about the location of the house to see its opportunities, a representative from the sales department could easily create the needed report to be delivered to the supply side participant based on his/her requirements. On the other hand, an employee from the product team could use SSBI to understand the interaction of the demand side participant – in this case it is the person intending to buy a house – with the platform and try to provide the most effective way of introducing a link between the supply and demand side for a successful transaction. Overall by focusing on the needs of supply and demand sides, we have identified that SSBI is an effective tool for various organizational units to design the most effective way for the platform participants to match with each other.

More Access and Freedom to Traffic Data and User Clickstreams

We have identified that SSBI is used to increase the functionality of the Finn.no platform by making it more efficient and more effective in responding to the needs of platform participants. Rather than focusing on participant level data, the primary focus here is on the aggregate level platform data. As an employee from a product department stated:

"...Through the self-service BI, I know how many people visit Finn.no, how many people visit Finn.no by mobile phone, and how many people visit Finn.no by tablet... How many page impressions are on Finn.no for a week..."

The focus on macro level data rather than micro level data is then used to improve the efficiency of the digital platform. To do so, an employee develops a certain hypothesis on how to modify a specific functionality, process or even change the location of a button/link on the digital platform to see how it may affect platform users positively and increase their satisfaction. A business developer mentioned:

"For example, if I would like to reallocate a button, and some people claim that it won't make a difference, we do some research and then I can claim that the user behavior is not the same, it's a different user experience and it will produce more clicks. So I use self-service to create an experiment using data and then hopefully my hypothesis is right. The result was that if we move it we will have 5-10% of more clicks and we will bring more value to the users."

Each employee who is responsible for the technical functionality and maintenance of the digital platform can leverage SSBI to improve the usage of the platform. In addition to the curation of individual level data, SSBI also plays a critical role in curating aggregate level data for better engaging with the platform's participants. Rather than meeting participants' needs directly, it contributes to the platform's agility by preparing an engaged "play field" for the participants to leave their digital footprints.

Fast Response to Requests

The dynamic nature of a digital marketplace requires its owner to be as responsive as possible to its participants' needs (Hagiu 2014). As one employee states:

"If people are not able to extract information on their own, then you need someone else to extract the data for them. If you don't give people the self service tools to analyze the information on their own, then they will need someone else to do it for them."

From that perspective, we have identified that SSBI has an impact on the time that it takes to respond to the requests of the platform's participants. As we have noted above, SSBI has impacted upon the interdependency levels among organizational units and such a change has created a shared fate and responsibility among these units. Furthermore, by democratizing the usage and manipulation of the collected data among the organizational units, SSBI enables the organization to give faster responses to both demand-side and supply-side participants to the extent that employees are confident of leveraging SSBI technology.

"And I do it as well, it's just sometimes I need to know if I am creating the reports correctly or not."

Contrary to the simplistic explanation that SSBI makes organizations more responsive within their respective business domains (Stodder 2015), we have found that this process is contingent upon the employees' ability to engage with the technology. Overall, by focusing on the time to respond factor, we have identified that the better an employee engages with SSBI, the faster he/she can respond to particular platform participants' needs. This is a particular advantage to a platform owner as it creates an option to be more facilitative towards platform participants (Van Alstyne et al. 2016) given that the company is successful enough to situate the SSBI technology within the company as it represents one of the intentional endogenous choices a keystone company can make (Augier and Teece 2008).

More Access and Freedom to Supply and Demand Navigation Behavior

We have identified that with the help of SSBI, employees can access different behavioral data about the participants of the Finn.no ecosystem. As one employee from the sales department stated:

"It makes it simple. You can create a dashboard where you can see how many people search different phrases on the Finn platform, you can see also how many people you reach. In one week Finn reached 45% of the population..."

In other words, SSBI gives employees the analytical tools (Chen et al. 2012) that they need to access participant data on different levels of depth and breath. This access then allows Finn.no to provide relevant product advertisements even when the demand side participants are not active on the Finn.no platform. As one employee stated:

"… If you are looking for an apartment in Oslo, maybe there was a period of a day or 2 days or 2 weeks where, for some reason, you did not visit the Finn.no site… People who have shown this behavior indicated that they are interested in an apartment in Oslo but have not visited the Finn platform during the last week. When we get a new apartment on our website and we think it is relevant for this user… we can show them an ad for that apartment when that user is visiting another site. Let us say that the user is visiting Facebook, we know the user, the type of apartment… We have this listing that is relevant for them…"

In other words, the Finn.no employees have an ability to exploit and explore participant data in different levels of depth and breadth while trying to figure out how to best design the mechanisms needed to match platform participants (Van Alstyne et al. 2016) using the analytical capabilities of SSBI. We have identified that the curation of digital data on a participant level constitutes an indispensable factor in enabling agility through providing a better linkage between Finn employees and the platform participants without direct interaction.

This highlights the importance of interdependence between demand side and supply side participants as one party's loss of interest in the platform could potentially result in other party's loss of interest as well. In such a situation, organizational agility plays an important role in the overall health of the ecosystem as it can potentially affect the core business; hence its competitive edge in the market (Iansiti and Levien 2004).

Operational Adjustment Agility

Nature of Relation with the Core Unit

The term "core unit" refers to the traditional organizational unit, which has been responsible for the report creation for the other organizational units. In our case, the IT/BI department has been the primary responsible organizational unit during the report creation process for handling the business operations of the company. Regarding the empowerment factor, we have been able to identify two main changes that SSBI has brought to the company. First, the reliance of other organizational units on the IT/BI unit has decreased, although not disappeared. For example, employees within the sales and product department can easily create their own reports based on their customers' needs without any reliance on the IT/BI unit. As a market researcher at the sales department states:

"… For us self-service is something we use to find the numbers we need. So it's just the easy way to get everything that we need without having to ask other people to do it for us. "

On the other hand, we observed that some employees still need guidance from the IT/BI department in some instances just to make sure they are creating the reports in a correct way. As one employee stated:

"Well I think self-service is really important when I need to find out information about customers. I no longer go to the BI department directly, now most of the time it is only to validate my reports"

Second, the IT/BI department has become less burdened by the other organizational units when compared to the traditional way of reports creation. We observed that due to this independence the IT/BI department can become more autonomous and place a greater focus on their core technical capabilities than when compared to the pre-SSBI era. A senior insight interpreter affirmed:

"I could say that, at least from our working perspective, the big push for implementing self-service BI here has been to free up capacity within the insight department. It has definitely reduced the ad hoc queries that we have to answer for the rest of the organizations. So it has freed up capacity for us to be more strategic and able to put more effort in further analytical questions, so rather than having to answer maybe 20-30 ad hoc questions, we actually now have maybe 5…"

Overall, we have identified that the level of the interdependency among organizational units has been impacted with the introduction of SSBI while the responsibility of each organizational unit has been increased and created a shared fate in dealing with the dynamic nature of the digital marketplace.

Empowerment

Self-service BI is designed to empower its users with the ability to become more data centric by allowing them to interact with data and information. A sales representative mentioned:

"I would say the biggest part of self-service BI is that it gives me more than what I had before. So where before I would use only one source of data, now it gives me more opportunity to combine insights and use more data available."

As a consequence of empowerment, employees are becoming more and more independent from other units in terms of report generation and data exploitation, which consequently affects their relationships with the core unit. A business developer stated in answer to a question about how often he refers to the IT/BI department for ad-hoc requests:

"Well, it used to be frequent as I have to answer many hypotheses in my work; currently I believe that I refer to them once every two or three weeks."

Having this empowerment and data exposure, employees are becoming more data driven in their relationships with different entities inside and outside the organization, which in turn promotes a more data driven ideology in the organization, hence enabling agility.

"If we are really truly to be data driven I don't believe that you will act intelligently on the only data you get you need to go and get it as well"

Data Access and Usage

The most fundamental change that has been brought about with the introduction of SSBI technology relates to the access of organizational data. The organizational users of SSBI can now access various sources of organizational data that they can leverage on to perform daily work-related activities, enabling more agility. Although it eliminates barriers in accessing data, it might create new difficulties in understanding and manipulating the data at the end user's side. To deal with this barrier, SSBI provides the ability to create a semantic layer[2] where the technical terms used in the database are linked to more convenient and understandable business terms.

"Employee X from our department has created a couple of self service models from different data sources that have Norwegian names and concepts and they would be more like business naming conventions…. We do this because everything in our data warehouse and external sources are based in English and the semantic models on top of it are kept in Norwegian to better support the users."

Following that, SSBI users can now access different data from different data sources enabling more agility in combining data from different departments such as sales and marketing for more insight and discovery.

"'I can create simple reports. I also can filter them by month, week, or even year but I am not an experienced user"

"It's very easy and I get predefined reports. So it's easy for me just to filter by year or month. Creating ad-hoc reports gets done a lot quicker with self-service as I am familiar with the language they use to describe the data or how they state it, so I can easily create reports just to see the real estate development, for example."

"I build my own reports. We also get a lot of Ph.D and masters students, or even journalists who want data for their articles… We have a dashboard that was created by our department called insight that creates it for us and which is easy to modify"

This evidence showed us that although SSBI technology is successful in terms of providing equal access to data it is not enough, per se, to fully exploit opportunities enabled by the SSBI. This increases the importance of having the necessary incentives to facilitate the learning process of users in regards to their engagement with the self-service capability of the BI technology. Therefore,

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[2] A semantic layer is "a business representation of corporate data that helps end users access data autonomously using common business terms. A semantic layer maps complex data into familiar business terms such as product, customer, or revenue to offer a unified, consolidated view of data across the organization." (Layer 2016)

organizations can benefit from the insights that employees develop with regards to various opportunities or problems.

We have identified that SSBI allows for the integration of several data source sets into a single visualization. In other words, data mash up ability has been provided to the employees so that they can create the reports they need independently of the IT/BI department. The data that the employees need is not necessarily stored in a single database; therefore it becomes a necessity to be able to combine several data sources into one coherent data structure depending on the needs of the employees. For example as one employee stated:

"If I want to do a chart analysis about company or industry size, I need to extract data through self-service. I need to match that with an extract from CRM as you need to see the industry the company is in. It's rare that I have all the data in one place so much of the time I do that by combining different sources."

In other words, organizational employees performing plug and play with several data sources can get new insights about their digital marketplace. This mash up flexibility, provided by the SSBI technology, then becomes the needed mechanism to better meet the demand and supply side requirements, therefore improving agility.

Discussion

Our study posed the question of how SSBI enables organizational agility in a multi-sided platform environment. Leveraging the two types of organizational agility identified by Lu and Ramamurthy (2011)– market capitalizing agility and operational adjustment agility –, we discovered which ways the SSBI enables these capabilities.

We focused on a multi-sided platform company, Finn.no, to explore the phenomenon of our interest. To our knowledge, the role of SSBI has not been explored in a multi-sided platform environment and that gave us an interesting opportunity to explore a context-dependent nature of organizational ability (Teece et al. 2016). The main challenge in operating in such a context is that the platform owner needs to constantly implement various incentives to the marketplace because the value creation and capture is contingent upon fulfilling the needs of customers, suppliers, regulators, governments, and other institutions (Evans and Schmalensee 2016). The requirement to consider various stakeholders at the same time, combined with the strategic considerations, calls on organizations to show agile capabilities – move faster relative to their competitors, adapt to changing requirements, and respond to emerging opportunities (Agarwal and Tiwana 2015).

On enabling *market capitalizing agility*, SSBI enables different organizational units to understand supply and demand needs based on their special interests and therefore target each stakeholder individually. In addition, since SSBI provides different organizational units with the ability to target various stakeholders, it raises the responsiveness of the platform owner to its environment. However, though the usage of SSBI decreases the interdependency between organizational units on their work processes, it does not eliminate that interdependency. It is also important for any employee to learn how to use and engage with SSBI so that he/she can leverage the opportunities provided by the SSBI system. Moreover, SSBI enables access to aggregate level platform data to keep the digital platform and its underlying infrastructure updated. Rather than focusing on the stakeholders' individual needs, SSBI helps in leveraging an individual stakeholder's footprint on the platform to further improve it. Finally, SSBI is an important instrument in matching the demand and supply sides of a multi-sided platform because it can provide detailed information about the interaction patterns of stakeholders on the digital platform and help to leverage that information to better design matching mechanisms (Van Alstyne et al. 2016).

On the other hand, on enabling *operational adjustment agility*, SSBI changes the interdependency levels of organizational units among each other when conducting their individual work which increases the flexibility among organization units and response time to requests and there appears to be a sign of change in organizational structures for the sake of more agile (Tallon and Pinsonneault 2011). In addition, SSBI empowers employees to make sense of data and therefore promote the data-driven culture (Watson 2009). Furthermore, the empowerment of organizational users is enabled because SSBI increases access to organizational level data and the possibility of creating various data mashup based on different requirements. In Table 3 below we summarize our findings in relation to the discussion and present how SSBI enables organizational agility.

Table 3: SSBI enabling agility		
Organizational Agility	SSBI enablement	
	What it enables	How it enables
Market capitalizing agility	Better understanding of supply and demand.	Through the diffusion of supply and demand needs to specialized units
	Fast response to requests	Through making each organizational unit capable of responding to user requests without any external reliance (IT/BI).
	More access and freedom to supply and demand navigation behavior	By the exploration and exploitation of supply and demand data generated though the multi-sided platform (macro level)
	More access and freedom to traffic data and user clickstreams	By the exploration and exploitation of supply and demand data (micro level)
Operational adjustment agility	Nature of relation with the core unit	Through the independence of IT/BI department
	Empowerment	By the ability to create ad-hoc reports and analytics.
	Data access and usage	Through the ability to perform data mashup and exploitation/exploration data.

Conclusion and Future Studies

In this study we have explored the role of SSBI in the digital marketplace by focusing on organizational agility. The use of technology is imperative in supporting data exploration and exploitation to support the many activities the employees perform in order to maintain a high level of competitiveness. Self-service business intelligence (SSBI) has shown, through our empirical study, to have an important contribution through several factors by enabling agility throughout the organization. In that context, this study contributes to the area of business intelligence by showing empirically how self-service business intelligence enables agility in organizations, especially in multi-sided platforms settings.

Future studies may expand the scope of our findings by investigating SSBI in other contexts, such as retail businesses where not all services provided to the customer are digital, to see whether the nature of the service plays a critical role in the relationship between SSBI and agility.

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Self-Service Business Analytics and the Path to Insights

Imad Bani-Hani has a background in information system and computer science. Before pursuing his PhD studies, he held the role of technical team leader, information system consultant and business intelligence specialist.

He holds a Bachelor of Science degree in computer information system and a Master of Science in information system from Lund University. His current research focuses on business intelligence and analytics with a particular interest in self-service analytics and the democratization of analytical capabilities in organizations.

In his dissertation, he explores Self-Service Business Analytics in organizations with a special focus on the Digital Marketplace industry. He mainly addresses two basic but important dimensions namely the internal self-service environment of the organization and the data to insight generation process. In the first, he describes how such environment is enabled to support insight generation and the later describes resource integration patterns and the engagement modes that leads to insights hence informed decision making.