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ANALYTICS AS A SERVICE: CLOUD COMPUTING AND THE TRANSFORMATION OF BUSINESS ANALYTICS BUSINESS MODELS AND ECOSYSTEMS

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Research paper

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Abstract

Due to the growth of data volumes, volatility and variety, business analytics (BA) become an essential driver of today's business strategies. However, BA is mainly adopted by large enterprises because it may require a complex and costly infrastructure. As many companies strive to make better use of their data and to adopt data-driven management paradigms, cloud computing has been discussed as a cost-effective approach to BA implementation challenges. To date, there has been little attention on the emerging class of analytical cloud services, "Analytics as a service" (AaaS). This article aims at demarcating AaaS as a cloud offering through an explorative research approach based on multiple case studies. Based on the analysis of 28 AaaS offerings, we derive a classification scheme for AaaS business model configurations and derive five business model archetypes. We discuss cloud computing's implications on the business analytics ecosystem where partner networks play an important role at all levels. By clarifying the definition and characteristics of AaaS business models, our study contributes to the 'Theory for Analyzing' that lays the groundwork for future research.

Keywords: business analytics, analytics as a service (AaaS), business models, business analytics ecosystem, cloud computing

1 Introduction

Owing to the growth of data volume, volatility and variety (*big data*), business analytics (BA) has become a key success factor for today's enterprises (Arun et al., 2015). BA comprises the use of analysis techniques over data resulting from business processes to derive managerial decisions, and it has traditionally been the focus of decision support systems (DSS), data warehouses, and business intelligence (BI). However, the implementation and integration of BA in organizations has proven to be challenging, since it may require a complex and costly infrastructure (Baars and Kemper, 2010). Various authors (e.g., Demirkan and Delen, 2013; Sun et al., 2012) show that analytical solutions are mainly adopted by large enterprises and argue that cloud services provide a cost-effective approach to support its adoption by a wider range of organizations. In fact, the global analytics as a service (AaaS) market is expected to grow from $5.9 billion in 2015 to $22.24 billion in 2020 (ResearchandMarkets, 2016), with an increasing share for predictive and prescriptive analytics (Gartner, 2016a).

Despite its high potential, the concept of AaaS remains vague, and a clear definition is lacking. The few existing studies have investigated how on-premise analytical applications, such as decision support systems (Demirkan and Delen, 2013), BI (Baars and Kemper, 2010), or big data analytics (Zulkernine et al., 2013), are migrating towards the cloud. These studies reveal that AaaS is a multifaceted concept that can be associated to the cloud service layers in different forms to serve different purposes and stakeholders. For instance, AaaS can be a data mining or reporting application for business end-users as a software as a service (SaaS) offering, but also a platform as a service (PaaS) offering that provides data scientists and developers with a data analysis suite or framework for their development. Finally, AaaS can be linked to infrastructure as a service (IaaS) that provides virtualized resources to host vast amounts of data and to perform targeted analysis. As an emerging cloud offering, AaaS imposes challenges on existing software vendors and their traditional BMs, while creating opportunities for new BMs. This article seeks to demarcate AaaS as a cloud offering and lay a foundation for future research. We ask the following research questions: **(RQ1)** What are the characteristics of AaaS BMs?, and **(RQ2)** which typologies exist in the market of cloud analytics?

To answer these questions, we apply case study research methodology and analyze 28 AaaS offerings. This research methodology is well suited for the investigation of complex real-world phenomena in their natural context (Benbasat et al., 1987; Yin, 2003), and has also been used by other authors to study cloud service BMs (Antero et al., 2013; Ojala and Tyrvainen, 2011). Our study adds to the literatures of BA and cloud BMs via two distinct contributions. First, by examining the emerging BMs of 28 AaaS offerings, we provide insights into the AaaS market and help to better demarcate AaaS. Second, based on a classification scheme characterizing AaaS BM configurations, we analyze the patterns and derive BM archetypes for AaaS. As an implication, we discuss different strategies for building AaaS-related capabilities and innovative BMs, along with their implications for existing value chains and ecosystems in the IT industry.

The remainder of this article is structured as follows: We start by clarifying the definition of BA and elaborate on BIA architectures before reviewing the current state of literature on AaaS. We then motivate our case study research approach and present the essential steps in our research process. The results section focuses on the key findings, the classification scheme, and the AaaS BM archetypes. We conclude by providing a synthesis of our findings and their implications.

2 Literature Review

2.1 Business Analytics: From BI to Big Data Architecture

Business analytics is concerned with "the extensive use of data, statistical, and quantitative analysis to support management decisions and actions" (Krishnamoorthi and Mathew, 2015). BA is defined in three main categories (Delen and Demirkan, 2013; Watson, 2014): descriptive, predictive, and prescriptive (see Table 1). Descriptive analytics, also denoted as business reporting, focus on historical data and their analysis to identify problems or opportunities. It comprises standard periodic reporting as well as ad hoc reporting, but also interactive reporting using online analytical processing (OLAP) tools for the multidimensional analysis of aggregated quantitative data. Predictive analytics help one to identify patterns and future trends based on past and current data using a wide range of data mining and advanced analytics tools. It is typically associated with techniques such as regression analysis, machine learning, and neural networks, which have existed for some time (Watson, 2014). Prescriptive analytics seek to improve business performance by determining a set of "alternative courses-of-actions or decisions given a complex set of objectives, requirements, and constraints" (Delen and Demirkan, 2013). It relies on mathematical modeling, optimization, and simulation models as well as expert systems and decision modeling tools.

The traditional way to implement BA is via BI solutions. A typical BI infrastructure comprises several components spread over a three-layer architecture: the data layer, the logic layer, and the access layer (Baars and Kemper, 2008): The *data layer* constitutes the storage and integration of structured and unstructured data. While structured data can be extracted with extract-transform-load (ETL) tools from operational systems (e.g. from ERP or other business applications), the unstructured data is mostly stored in content management systems and document management systems. The *logic layer* has different components that allow one to refine and analyze the data. The typical BI components on this layer are tools for database querying and reporting (e.g. SAP ERP, Oracle ERP, etc.), for multidimensional data analysis (e.g. OLAP), and for data mining (e.g. predictive analysis, text mining, web mining) (Sun et al., 2015). The *access layer* is needed to combine and present the results to users, for instance, using a portal infrastructure that integrates different analysis components.

Categories	**Questions**	**Goals**	**Techniques**
Descriptive analytics	What has happened?	To discover business opportunities and problems	Standard/ periodic business reporting, ad hoc/ on-demand reporting, dynamic/ interactive reporting, OLAP, slice and dice, drill-down/roll-up
Predictive analytics	What will happen and/or why will it happen?	To discover explanatory and predictive patterns (trends, associations, affinities, etc.)	Data mining, text mining, web/ media mining, statistical time series forecasting
Prescriptive analytics	What should I do? Why should I do it?	To determine a set of high-value alternative courses of action or decisions, given a complex set of requirements and constraints	Optimization, simulation, decision modeling, expert systems

Table 1. Taxonomy of business analytics, based on Delen and Demirkan (2013)

The emergence of big data increases the volume, variety, and velocity of data (Watson, 2014). It is not possible to incorporate the huge amount of (real-time) data generated by business processes, social, mobile, or sensor data via the traditional BI architecture. Since big data is injecting new components and technologies, Ereth and Baars (2015) have updated the traditional BI architecture which suggests a more comprehensive business intelligence and analytics (BIA) architecture: In the data layer, new data repositories are required to handle the vast amount of data. These big data stores leverage frameworks such as Hadoop or Spark for distributed storage and distributed processing of very large datasets on computer clusters (Watson, 2014). In the analysis layer, BI and big data analytics share common components. However, big data analytics introduces new technologies and components, for instance for handling streaming data or analyzing data from social media using network analysis (Sun, 2015).

Given its complex architecture, the implementation of BA is considered to be costly and can mostly only be afforded by large enterprises (Sun et al., 2012). In fact, the deployment of BIA solutions requires high investments in hardware infrastructure and expensive analytics software. In addition, the big data trend is creating more challenges for such implementations owing to the new technologies required for the storage and processing of huge amounts of data (Ereth and Baars, 2015; Arun et al., 2015). This calls for cost-effective solutions that allow for the adoption of analytics by small and medium-sized enterprises (SMEs), and reduces cost and complexity for larger enterprises.

2.2 Analytics as a Service: An Emerging Cloud Offering

The cloud delivery model has been explored as a solution for BA implementation challenges concerning hardware and software complexity and cost (Baars and Kemper, 2010; Ereth and Baars, 2015; Sun et al., 2012). Besides the reduced costs for implementation, several other factors favor cloud services for BA, particularly increased agility owing to the scalability of cloud. AaaS has been coined for cloud services in the analytics realm. Several researchers have begun to explore the cloud analytics landscape using different perspectives: The first research stream proposes and pilots innovative cloud architectures and services as research prototypes, while the second analyzes how different analytical application classes (BI, DSS, and big data) are migrating towards the cloud.

In the first research stream, Sun et al. (2012) propose *analytics cloud* as a cost-effective approach that leverages the SaaS delivery model to provide analytics capabilities. They develop a framework for AaaS and address two critical technical issues for achieving cost-effectiveness: (1) multitenancy enablement so that a single software instance can effectively support multiple concurrent tenants, and (2) the customization of service-level agreements (SLAs) to satisfy tenants' diverse analytics capability demands. Zulkernine et al. (2013) suggest a conceptual architecture of CLAaaS, a cloud-based AaaS platform for big data analytics. CLAaaS is explicitly designed as PaaS, not as a single system, that will be configured with several analytic systems to provide “on demand data storage and analytics services through customized user interfaces which will include query, decision management, and workflow design and execution services for different user groups”.

In the second research stream, different authors have developed scenarios and conceptual models of the AaaS landscape for diverse analytical application classes. For BI, Baars and Kemper (2010) develop a framework that can help one to identify, combine, and eventually evaluate potential BI services. They derive six scenarios for cloud BI. According to them, it can be composed of independent components or a combination of functional BIA blocks having different delivery service models, but these scenarios are not further validated. Alternatively, Demirkan and Delen (2013) propose a conceptual framework for DSS in the cloud. They decouple AaaS with its data analytics and visualization capabilities from data storage (data as a service) and data integration (information as a service). For big data analytics, Arun et al. (2015) develop a model for a platform covering “capabilities of an analytical solution, from data acquisition and management to business-user visualization, reporting and interaction”. Moreover, Sun et al., (2015) propose big data analytics services-oriented architecture (BASOA) for descriptive, predictive, and prescriptive analytics, and highlight the common features as well as complementarities of BI and big data analytics.

AaaS literature also elaborates on two primary user groups: data experts and business users (Arun et al., 2015). Data experts could be data integrators or data scientists that deal with technical aspect of analytics systems concerning data acquisition, modeling, and workflow design. Business users are typically practitioners and managers who are more interested in the business value of analytics concerning query results, visualization, and collaboration. Controlling data access for different user types is a critical aspect of analytics applications; thus, an SLA component is required to support the different roles or stakeholders for AaaS (Delen and Demirkan, 2013; Zulkernine et al., 2013).

2.3 Research Gap

With the growing importance of data, BA is a primary investment priority in companies. However, compared to other cloud offerings for business applications that are offered as SaaS (such as CRM or ERP systems), AaaS is a latecomer. From our literature review, we find that researchers have only begun to explore this phenomenon, but have mostly focused on designing key aspects of future AaaS architectures or exploring its landscape from the perspective of existing application classes moving to the cloud. While there is a growing understanding of AaaS architectures, no definition of AaaS has been proposed, and despite the growing number of AaaS offerings, we lack insights about the emerging categories of analytical cloud services. Based on our review of prior studies, we propose that AaaS should denote the analytical capabilities delivered in the cloud and it spans the different cloud capabilities and models required for BA to fit the expectations of different users and roles. It should be distinguished from cloud services on the data layer that are denoted as data as a service (DaaS). Given the complexity of BI and big data analytics architectures, component-based approaches that leverage service-oriented integration are recommended for a cloud-based BA environment.

3 Methodology

3.1 Research Approach

To study the emerging AaaS cloud offerings, we follow case study research methodology, which allows the investigation of complex real-world phenomena (Benbasat et al., 1987; Yin, 2003). Case study research is the preferred approach to study cloud based BMs to thoroughly analyze the value creation logic and has been used by different authors (Boillat and Legner, 2013; Kaltenecker et al., 2015; Kranz et al., 2016). For instance, Ojala and Tyrvainen (2011) examined how the migration of business applications towards the cloud impacts the vendors’ BMs, and Antero et al. (2013) conducted a case study on SAP's BM to explain its success based on "its ability to reconfigure its business model". According to Yin (2003), multiple case studies increase the validity of results, because patterns can be compared between cases and better generalization can be derived. We built our research on multiple case studies of existing AaaS offerings that would support the analytical generalization of our findings.

3.2 Case Selection & Data Collection

In selecting our cases, we focused on instrumental case studies that would advance our understanding of existing and emerging AaaS BMs. We used theoretical sampling, since we focus not on theory testing but on the examination of concepts and theory building (Eisenhardt and Graebner, 2007). Our goal was to come up with a case sample that covered all relevant dimensions for exploring diverse AaaS BM configurations: (1) the AaaS offering's functional scope, (2) the cloud delivery model or the layer addressed by the offering (i.e., SaaS, PaaS or IaaS), and (3) the provider type. To allow for variation in the first dimension, we included cloud services that address one or more aspects of BA, i.e. descriptive, predictive, and prescriptive analytics. For the second dimension, our sample is diverse concerning the different cloud layers, because it has been shown that the software business becomes a platform business (e.g., GoodData as a self-service analytics platform). Related to the third dimension, our sample covers incumbents who are moving to the cloud as well as 'pure' cloud players. It is important to consider both vendor types, since research has shown that significant differences exist between pure cloud players who introduce novel offerings in the market and on-premises providers seeking to migrate their existing, often comprehensive offerings to the cloud.

We addressed case identification and selection in three steps: In step one, we conducted a market analysis of existing cloud analytics offerings and their BMs to compensate for the lack of academic contributions on the topic. Since our goal was to get an exhaustive overview of existing AaaS offerings and vendors, we reviewed listings of BI, advanced analytics, and big data products in analysts' reports, including Gartner (Gartner, 2016a,b), Forrester (Forrester, 2015, 2016), Research-and-Markets (ResearchandMarkets, 2016), and IT and business magazines articles, including from *InformationWeek* (Henschen, 2015) and *Forbes* (Marr, 2016). We were able to identify 88 software vendors (some were acquired by larger vendors during our study) with 98 analytics offerings. In step two, we classified these offerings as cloud-based or on-premises. In step three, we prioritized cases and selected 21 vendors with 28 offerings for further analysis. Here, we based our selection on a vendor's appearance frequency in reports and articles, selecting the providers with a frequency score of more than or equal to 2. This ensured that we included only robust offerings in our sample.

We based data collection on a thorough exploration of secondary data from vendor and third-party sources. We collected information on each case from product information provided on a vendor's website, including documentation, factsheets, training material, and demos that provide detailed insights into the AaaS offering and its characteristics. We also used the company website to get information about the vendor and the business type(s) it is involved in (i.e. enterprise systems vendor, analytics vendor, or pure cloud vendor). As additional third-party information, we used the analysts' reports and magazine articles identified in the selection process, as well as media releases and news articles related to the offerings. Relying on a variety of different data sources allows for data triangulation and increases the validity of our analysis (Yin, 2003).

3.3 Case Analysis: Analysis Framework and Coding

For within-case and cross-case analysis, we developed an analysis framework that builds on established BM conceptualizations to support a structured analysis and classification of AaaS BMs and to contribute to the wider body of cloud BMs. Following the classification, we identified recurring patterns of attributes that we group to define the AaaS archetypes.

For analyzing the offerings, we opted for the Osterwalder and Pigneur (2010)'s Business Model Canvas, which has been developed based on an ontological analysis of BM conceptualizations. It comprises nine interconnected components that allow for the integration of disparate strategic perspectives. From the value creation side (customer and market perspective), the BM components comprise *customer segments* that are served, a *value proposition (VP)* offered to satisfy customer needs, the *channels* chosen to reach customers, *customer relationships*, which establish the relationships between the VP and customers, and the *revenue streams* chosen to perceive financial entries. On the resource base and value configuration side (company and internal perspective), the BM components are *key resources* and *key activities* needed to run the business, *key partners*, who are necessary to deliver the VP, and the *cost structure*. Moreover, the framework included additional information related to the provider business type, and the cloud delivery model.

Based on the data collected about the AaaS vendors and their offerings, two authors coded each AaaS offering based on the analysis framework. We divided the case material between the authors before we undertook the analysis. One author first analyzed and coded each case. To increase interpreter reliability, a second author then analyzed each case. If there was agreement on the coding, the codes were accepted. The authors then further discussed and validated the codes. After consolidating the results of the coding and ensuring data quality, we analyzed our dataset concerning our research questions. The final list of codes and subcodes serves as a classification scheme for AaaS offerings that helps us to analyze their BM configuration. Using pattern-matching, we looked for within-group similarities and between-group differences of selected categories to search for consistent patterns among cases (Yin, 2003).

4 Results: AaaS Business Models and Archetypes

4.1 A Classification Model for AaaS

Based on the analysis framework, we derived a classification scheme (Fettke and Loos, 2003) from our analysis of the 28 cases, to characterize AaaS offerings (Table 2). A classification scheme "categorizes phenomena into mutually exclusive and exhaustive sets with a series of discrete decision rule" (Doty and Glick, 1994). The main classification categories are derived from the analysis framework and comprise the BM components as well as the cloud deployment model. We derived the subcategories from our bottom-up analysis of the AaaS offerings[1].

Customer segments: Our case analysis confirms business users and data experts as the primary AaaS user groups, but provides a more detailed classification with four distinct customer segments targeted by AaaS: (1) *Business users* across teams, functions, and divisions are able to explore data and benefit from self-service analytics. (2) *Business analysts* can benefit from the self-service feature to prepare their needed reports and analytics. They benefit from the reporting and visualization capabilities and they mainly correspond to SaaS users. (3) *Data scientists* and *integrators* can create data models and workflows to analyze the data they are targeting. *Developers* can build applications with analytical capabilities on the AaaS platforms. These users are mostly associated with PaaS analytics offerings that leverage the development capabilities of such cloud services types. (4) *IT architects* are another user type and are responsible for managing and configuring the data sources (data processing) and can benefit from scaling the infrastructure to the cloud leveraging the IaaS value proposition of AaaS.

Value proposition: AaaS offerings' *core VP* is built around the data sources and the services throughout the analytics lifecycle, from the data processing to the analysis and visualization. It can be

1 Given the lack of information available on certain business model components, our classification scheme includes all aspects of the value creation side, but only selected components of the resource base and value configuration side. Most importantly, we were unable to derive the cost structure.

associated with SaaS. Besides the core value, AaaS can provide additional embedded value propositions. Certain offerings provide substantial data storage capabilities or platform capabilities. We denote them as *infrastructure VP* and *platform VP*.

The classification of the **core VP** is thus dependent on the data types and the different stages of the analytics lifecycle. AaaS services differ concerning the data sources they support and thus the processed data type. These can be typical *business data*, as structured data (e.g. financial, sales, or customer data) and documents (e.g. text or images) from traditional enterprise systems and databases. Emerging cloud offerings also integrate *big data* sources, which are categorized as structured, semi-structured, and unstructured data from web, mobile and social media, location-based data, and *streaming* (or real-time) data from sensors, devices, and connected machinery via the Internet of things (IoT). For the analytics stages, the classification covers the data processing and preparation (P&P) step, describing the specific techniques for data integration related to the data type used. AaaS services typically use ETL technology and data warehousing for traditional business data, or dedicated services for processing big data such as Hadoop and Spark. This is closely related to the infrastructure offerings that the vendor provides; AaaS providers can have their own *infrastructure* to support their offerings (as embedded **infrastructure VP**) or can use connectors to data sources and perform *data integration*. Once the data is prepared, cloud services come into play for the analysis step. They support *descriptive analytics* with basic query for simple reporting or OLAP for multidimensional reporting, *predictive analytics* – including statistical and predictive modeling, machine learning, data mining, text mining, and location mining – as well as big data analytics that involve sentiment analysis of social media data as well as real-time analytics, and *prescriptive analytics* for optimization and simulation which are mostly used in the manufacturing industry and can be applied to data from connected devices. Finally, AaaS services provide data visualization that corresponds to a data access layer. It is based on three aspects: *representation forms* such as dashboards or location maps, *interfaces* involving desktop, mobile access, or interactive boards, and a *collaboration* component.

For the PaaS offerings, we distinguish two groups of additional **platform VP**: *development platform* for building analytics-intensive applications and application-based *integration* for platforms that allow integration with partner technologies and software. Typical development platforms allow building analytical applications through offering advanced analytical algorithms and models. These PaaS offerings target data scientists and developers as their customer segments. Another type of development platforms allows users to author simple analytical applications (i.e. to generate reports and dashboards) and to share the results and insights.

Customer relationships: In the traditional software delivery model for enterprise applications, partners in particular integrators, and software vendors play an important role in maintaining relationships with customers. With cloud computing, AaaS vendors attempt to transfer their customer relationships to online channels, but these rather complement than replace the traditional partners. Online customer relationships rely on online customer portals and communities, and support product evaluation through live product demos and trial versions. In addition, vendors provide customer support as traditional means to maintain customer relationships through a typical support team or integrators mainly for PaaS offerings.

Channels: We categorized the channels through which the AaaS providers get in touch with their customers as direct and indirect. Direct channels correspond to the AaaS vendors' sales and service units for direct contact, and online channels such as the provider's website or portal. Indirect channels are mainly composed of partner networks and represent a larger part of overall software sales for traditional BI and big data analytics. Although cloud services aim at leveraging online channels, most AaaS solutions cannot be used without any direct interaction or the support of service providers to configure and implement the software. As a result, direct channels such as sales representatives, but also indirect channels such as partners, remain important for supporting companies in the evaluation and implementation process. For AaaS, we identified different partner programs that represent a channel for reaching customers directly as re-sellers and referral partners, or indirectly through an embedded product through technology partners.

Partnerships: Partner networks play a key role in shaping AaaS offerings. Most AaaS providers rely on a variety of technology partners that enable and support their analytics capabilities and enhance their user-fronted representation. In addition, most offerings benefit from original equipment manufacturer (OEM) partners who embed an analytics component within their products (hardware or software) and independent software vendor (ISV) partners who employ embedded analytics or provide analytics solution leveraging their capabilities in the case of platform offerings. Other partners are the system integrators (SI) who provide support and consulting services to AaaS providers' customers. Additionally, resellers and referral partners represent an indirect channel for creating revenues.

Revenue streams: As with other cloud services, the main revenue stream is subscription-based. Most offerings provide subscriptions, which are per user and possibly per computing hour for big data offerings, and per storage capacity. In the latter case, editions are an option for self-service analytics providers that support big data types. So, a basic subscription is offered, along with a big data edition as a plus. Further, companies that provide platform capabilities mostly offer additional training services as another revenue stream. The channel partners can also be considered as a significant revenue stream for most offerings (e.g., resellers and OEMs).

Vendor	AaaS offering	Category	Core VP										Embedded VP				Customer Segment	
			Data Sources			P&P	Analysis			Visualization			Platform			Infra-structure		
			Business Data	Streaming Data	Mobile, web & social	Data Integration	Descriptive	Predictive	Prescriptive	Visual discovery and exploration	Mobile interfaces	Sharing & Collaboration	Development	App integration	Distribution channel	Specialized infrastructure (e.g., in-memory, big data)	Business users & analysts	Technical users
Bime	Bime	V	●		◑	●	●			●	●	●					●	
Qlik	Qlik Sense Cloud	V	●			●	●			●	●	●					●	
Tableau	Tableau SaaS	V	●			●	●			●	●	●					●	
Adaptive Insights	Adaptive Suite	S	●			●	●	◑		◑	●	●					●	
Birst	Birst	S	●		◑	●	●	◑		◑	●	●					●	
GoodData	Gooddata platform	S	●			●	●	◑		◑		●	◑		◑		●	◑
IBM	IBM Cognos Analytics	S	●			●	●	◑		◑	●	●					●	
Information Builders	WebFOCUS BI and analytics platform	S	●			●	●	◑		◑	●	●	◑			◑	●	◑
Microstrategy	Microstrategy	S	●		◑	●	●	◑		◑	●	●					●	
Oracle	Oracle BI Cloud Service	S	●			●	●	◑		◑	●	●					●	◑
Salesforce	Wave Analytics	S	●			●	●	◑		◑	●						●	
SAP	SAP BusinessObjects Cloud	S	●			●	●	◑		◑	●	●				◑	●	
SAP	SAP Digital Boardroom	S	●			●	●	◑		◑	●					◑	●	
SAS	SAS Visual Analytics	S	●		◑	●	●	◑		◑	●	●					●	
TIBCO Software	TIBCO Spotfire Cloud	S	●			●	●	◑		◑	●	●					●	
Amazon	Amazon Quicksight	S	●			●	●	◑		◑		●				◑	●	●
Microsoft	Power BI	S	●			●	●	◑		◑	●	●					●	
1010data	Insights Platform	P	●		◑	●	●	●		◑			●			●		●
IBM	IBM Watson Analytics	P	●		◑	●	●	●		◑			●					●
SAP	SAP HANA Cloud Platform	P	●		◑	●	●	●					●	●		●		●
Predixion Software	Predixion RIOT	E		●		●		◑	●	◑			●	●			◑	●
Microsoft	Azure (Intelligence + Analytics)	B	●		●	●		●		◑			●	●	●	●		●
Alpine Data	Chorus 6	B	●		●	●		●			●	●	●			●	◑	●
Altiscale	Insight Cloud	B	●		●	●		●		◑		●				●	●	◑
Altiscale	Data Cloud	B	●		●	●										●		●
Oracle	Oracle Big Data Preparation Cloud Service	B	●		●	●		●		◑						●	●	◑
Oracle	Oracle Big Data Discovery Cloud Service	B	●		●	●		●		◑		●				●	●	
Qubole	Qubole Data Service	B	●		●	●		●					●	●		●	◑	●

Legend: ◑ partially covered ● fully covered

Table 2. Classification and Categorization of AaaS Vendors – Value Propositon and Customer Segments (Extract)

4.2 Archetypes of AaaS Business Models

We identified BM patterns and derived five AaaS archetypes. Compared to the classification scheme, archetypes represent a typology. According to Doty and Glick (1994), typologies identify multiple ideal types, each of which represents a unique combination of the attributes. Several guidelines have been derived for developing typologies. Most importantly, the assumptions about the theoretical importance of their first-order constructs must be clear and they "must provide complete descriptions of each ideal type using the same set of dimensions" (Doty and Glick, 1994). We present these archetypes with their BM characteristics, and illustrate them with representative case studies (Table 3).

AaaS	Visualization as a service	Self-service AaaS	Analytics PaaS	Big data AaaS	Edge AaaS
Representative cloud services	Tableau Online	GoodData	SAP HANA Cloud Platform	Qubole Data Service	Predixion RIOT
Value proposition	·Visualization ·Dashboards ·Mobile ·Collaboration ·Data integration	·Visualization ·Dashboards ·Reporting ·Basic Predictive analytics ·Mobile ·Collaboration ·Data integration	·In-memory database ·Predictive analytics ·Advanced analytics ·Spatial analytics ·Text mining ·Data integration ·Development ·Application integration	·Predictive analytics ·Machine learning ·Hadoop/Spark ·Smart query ·Data integration ·Development ·Application integration	·Real-time analytics (IoT) ·Advanced analytics ·Predictive analytics ·Data integration ·Development
Customer Segments	·Business users	·Business users ·Business analysts ·Data scientists	·Data scientists ·Developers ·IT architects	·Business analysts ·Data scientists ·Developers ·IT architects	·Business users (industry-specific) ·Data scientists ·Developers
Customer Relationships	·Training ·Webinars ·Support ·Customer portal	·Blog ·Training ·Webinars ·Customer portal	·Blog ·Support ·Training	·Blog ·Community ·Support ·Training	·Blog ·Library ·Support
Partnerships	·Re-sellers ·Technology ·OEM	·Technology ·OEM ·Application development	·Application development ·OEM ·SI	·Technology ·SI	·Referral ·Resellers ·Technology ·OEM
Channel	·Online ·Live demos ·Partners: OEM, resellers	·Live demos ·Direct contact ·Partners: OEM	·Online ·Trial ·Direct contact	·Online ·Trial ·Direct contact	·Direct contact ·Partners: OEM, resellers, referral
Revenues	·Per user	·	·Per user ·Per storage	·Per user ·Per computing hour	

Table 3. AaaS Archetypes with Representative Case Studies

1) Visualization as a service: This archetype targets end-users interested in visualizing their data and getting quick insights. It provides visualization (i.e. charts, graphics, and plots) and data discovery capabilities with basic reporting. However, essentially, no analytics algorithms and models are provided. Innovative offerings introduce interactive reporting and discovery in new contexts (e.g. digital boardrooms), new ways of visualization (e.g. map), and dashboards. This type of AaaS allows for the integration of data from different applications with the possibility of live connection to cloud data sources. The collaboration is also an important aspect, since it allows for sharing insights among teams and groups. A prominent example of this category is Tableau Online, also Bime and Qlik Sense Cloud, which offer access to multiple data sources and interactive dashboards in a SaaS delivery model.

2) Self service analytics as a service: This archetype offers self-service analytics for business users and analysts who are able to easily access data from multiple sources as a replacement to data warehousing. They can perform descriptive and basic predictive analytical jobs, including multidimensional reporting and statistical modeling. Typical vendors in this category are established BIA vendors who leverage their domain expertise to offer self-service analytics software on the cloud, such as SAS and Microstrategy. Other vendors involve new entrants, with Birst as a prominent example or GoodData that leverages PaaS VP to offer self-service analytics.

3) Analytics Platform as a service: This archetype offers advanced analytics algorithms and techniques to assist data scientists in processing and modeling data. This type of AaaS is mostly associated with in-memory database offerings. It provides a development environment for building specialized analytics applications with advanced capabilities. This involves a suite of machine learning algorithms and predictive analytics, including advanced data mining (e.g. text and spatial). It provides platform capabilities concerning development and application integration for specialized users.

4) Big data AaaS: This archetype provides big data infrastructure and data management resources for taming and processing big data. It provides comprehensive platform capabilities and data management for big data sources, such as Hadoop. Besides the data processing, the platform provides advanced analytics capabilities, including advanced data mining for text, spatial, and social media data as well as machine learning algorithms for big data applications and insights. These offerings come in the different cloud service forms. Altiscale Insight Cloud is an analytics software built on top of Altiscale Data Cloud, which is a big data infrastructure service that runs Hadoop and Spark for data processing and management. Qubole is another offering that combines data preparation and integration from big data sources and big data analytics as a platform service.

5) Edge analytics as a service: This emerging archetype focuses on advanced analytics capabilities for IoT platforms. It provides special infrastructure of data storage and real-time data processing to allow the analysis of streaming data from connected devices. It offers analytics on the edge, i.e., real-time analytics are delivered closer to the end-users of connected devices. Specifically, visual analytics are provided on devices and gateways, providing analytics at the source of data for swift actions. It also provides an environment that supports prescriptive analytics for data modeling and application development on the cloud platform. As an emerging category, only a few offerings are yet available on the market, with Predixion being considered as a visionary in this domain.

5 Synthesis & Discussion

Our empirical findings reveal a landscape of specialized offerings with dedicated VP and customer segments. They thereby undermine a uniform view of AaaS and demonstrates that AaaS extends the VP of traditional BIA solutions beyond only migrating infrastructure and algorithmic capabilities to the cloud. While the archetypes ‘visualization as a service’ and ‘self-service AaaS’ focus on mostly descriptive and basic predictive capabilities targeting business users and analysts, they emphasize visualization and collaboration capabilities to support their user communities in sharing analytics results. The remaining three archetypes target experts, notably data scientists and developers, that seek to leverage prescriptive and predictive techniques, including machine learning, simulation and optimization to analyze a variety of data sources, covering big data, and real-time data analysis. The IoT paradigm drives new AaaS BMs such as edge AaaS that provide real-time analytics for the data streams generated by sensors, connected devices and machines. Table 4 presents an overview of the AaaS landscape, providing BM characteristics of the archetypes identified in the previous section.

With regards to the cloud delivery models, the analysis reveals AaaS BMs that cross the traditional cloud service layers. While AaaS offerings provide their core VP mostly as SaaS in the cloud, certain archetypes comprise additional embedded VPs. While platforms become a very common trend in software business, the AaaS related platform VP is interesting because it provides development environment for analytical applications to data scientists and developer communities. As outlined in prior literature on PaaS, the emerging multi-sided BMs (for AaaS platforms, big data and edge) require AaaS vendors to create a flourishing ecosystem around the platform with a win-win-win situation for customers, developers, and themselves. As four out of five AaaS archetypes do not integrate infrastructure-related cloud services, our analysis confirms Delen and Demirkan (2013)’s definition of the AaaS layer building on DaaS, while we cannot find evidence of dedicated IaaS offerings and BMs. On the other hand, big data AaaS integrates specific cloud storage infrastructure. As this archetype integrates analytical capabilities directly in the data storage, it spans all cloud delivery layers.

BM Components		Visualization as a service	Self-service AaaS	Analytics PaaS	Big data AaaS	Edge AaaS
Value creation	Value proposition	Interactive data exploration and discovery	Easy access to data with descriptive and basic predictive analytics capabilities	Advanced analytics-capable application development	Big data processing and insights	Real-time data analytics on connected devices and prescriptive analytics capabilities
	Customer segments	Business users	Business users, business analysts, and data scientists	Specialized users: data scientists, developers, and IT architects	Business analysts, data scientists, developers, and IT architects	Industry-specific business users, data scientists, and developers
	Customer relationships	Community, training, and traditional customer support	Community, training, and traditional customer support	Community, training, traditional customer support, and consulting	Community, training, traditional customer support, and consulting	Training, traditional customer support, and consulting
	Channels	Direct channels & indirect channels: resellers, OEMs	Direct channels & indirect channels: re-sellers, OEMs	Direct channels	Direct channels	Direct channels & indirect channels: resellers, OEMs
	Revenue streams	Subscription per user, per data storage, and partner network	Subscription per user, per data storage, and Partner network	Subscription per user, per data storage, additional services, and partner network	Subscription per user, per data storage, per computing hour, additional services, and partner network	
Resource-based and value configuration	Key resources and activities	Possesses domain and visualization expertise	Both domain expertise (to include best practices) and application development capabilities	Both domain expertise (to include advanced analytics) and application development capabilities + In-memory databases	Both domain expertise (to include advanced analytics) and application development capabilities + Big data infrastructure	Both domain expertise (to include advanced analytics) and application development capabilities + IoT platforms with sensor networks infrastructure
	Key partners	Technology partners for infrastructure and analytics capabilities and other AaaSs for offering embedded solutions	Technology partners for infrastructure and visualization, and IT service providers for offering embedded solutions	IT service providers for application development and integration partners for support services	Technology partners for visualization, IT service providers for application development, and integration partners for support services	Technology partners for infrastructure and visualization, and integration partners for offering embedded analytics
Delivery Model		SaaS	SaaS or PaaS	SaaS and PaaS	SaaS and PaaS	SaaS, PaaS or IaaS

Table 4. Business Model Characteristics of AaaS Archetypes

From the perspective of software vendors, the five AaaS BM archetypes can be associated with different strategies for building AaaS-related capabilities and innovative BMs as a standalone or complementary offering. For incumbents that migrate their on-premise BI solutions to the cloud, AaaS implies, according to our study, the strategic choice between offering self-service BI or becoming an advanced AaaS platform. Another option for vendors with specific expertise in databases or analytical techniques is to propose development environments for advanced analytical techniques and models as AaaS platforms. They thereby migrate into a platform business and their success will depend on their ability to create communities of data scientists and developers. Our analysis of channels and partner networks reveals significant changes in the BA ecosystem. Traditional BI architecture implied strategic partnerships between BI vendors with database and hardware vendors, as well as integration capabilities with different source systems. These eco-systems are currently being radically transformed by emerging collaboration ecosystems among cloud vendors to deliver a shared VP through integrating various offerings. It is achieved through combining capabilities throughout the analytics lifecycle; infrastructure capabilities for big data storage and processing, advanced analytics expertise, and interactive visualization and data discovery. With the new IoT paradigm, software vendors should cooperate with hardware suppliers to provide a technical infrastructure that can actually handle the real-time information for edge analytics. Further, for software vendors, the investments and competencies required to deliver an AaaS depends on the data infrastructure. Deploying analytics without the necessary infrastructure might be difficult; the vendor must either develop their own infrastructure (e.g. SAP HANA Cloud Platform) or limit their offering to specific applications and use cases running on one of the leading vendors' platforms.

6 Summary and Conclusion

Scholars have repeatedly called for more research on cloud computing's implications on the software industry (Veit et al., 2014), and our research is a response to this call focusing on the domain of BA. Our research objective was to demarcate the AaaS cloud offerings and explore the cloud's transformative power. This study presents two important contributions. First, by examining the emerging BMs of 28 AaaS offerings, we provide insights into the market of AaaS in the form of a classification scheme that supports describing and aiding analysis of the phenomenon of AaaS, based on essential BM components. Second, we derive BM archetypes for AaaS based on the identified classification patterns. These archetypes question the analysis of AaaS through the perspective of the traditional cloud delivery layers, and support the idea of AaaS as separate cloud service category that builds on data provisioning services (DaaS). By providing a classification and archetypes of AaaS BMs, the theoretical contribution of our study can be considered a Type 1 theory according to Gregor (2006)'s taxonomy of theory types in IS. As "theory for analyzing" it is the most basic theory resulting in taxonomies, classifications and typologies (Doty and Glick, 1994) and lays the foundation of future research.

AaaS is still an emerging concept and our findings represent the AaaS offerings as of autumn 2016, which adds some limitations to our study. Our qualitative research approach relies on information from public sources. This provided access to customer-facing elements in the vendors' BMs, but prevented an internal view in terms of cost structure and detailed resources and activities. Although we analyzed multiple case studies, our approach does not support statistical generalization, but allows for analytical generalization through our study design. The sample of cases covers all relevant dimensions of AaaS BM configurations including functional scope, corresponding cloud layer, and the vendor type. Accordingly, more empirical studies are encouraged in the field of AaaS BMs to validate our findings and to analyze the dynamics in the AaaS landscape.

As an implication of our research, we see promising avenues for future research on AaaS: the first avenue is the emerging cloud ecosystems for AaaS. As mentioned new partnership models and roles, such as OEMs, emerge for value co-creation in alliances between one or more AaaS vendors, infrastructure providers as well as a growing community of data scientists and developers for BA. This calls for research on BA ecosystems and could be studied through the lens of business networks, but also information supply chains. As second promising stream of research are AaaS platforms and their multi-sided platform BMs. Scholars could build on the recent publications on PaaS (Giessmann and Legner, 2016; Cusumano, 2010; Tiwana et al., 2016) to refine the definition of AaaS platforms and study how VPs should be designed for the different target segments. Finally, we suggest scholars to study not only the emerging BMs, but also incorporate the 'voice of the customer' by analyzing user preferences for AaaS. As implication for practice, our findings can help software vendors that target the BA market to transform their on-premise solution into a cloud-based offering. Software vendors can use the AaaS archetypes to shape crucial aspects of their cloud offering and define their future BM, as well as to evaluate their emerging ideas against these. Our findings highlight the importance of creating partnerships and carefully considering whether to become a platform provider or not.

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