Pathways from Data to Value: Identifying Strategic Archetypes of Analytics-Based Services

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Abstract. The digital transformation offers organizations new opportunities to expand their existing service portfolio in order to achieve competitive advantages. A popular way to create new customer value is the offer of analytics-based services (ABS) – services that apply analytical methods to data to empower customers to make better decisions and to solve complex problems. However, research still lacks to provide a profound conceptualization of this novel service type. Similarly, actionable insights on how to purposefully establish ABS in the market to enrich the service portfolio remain scarce. Our cluster analysis of 105 ABS offered by start-ups identifies four generic ABS archetypes and unveils their specific service objectives and pronounced characteristics. The findings contribute to a more profound theorizing process on ABS by providing a detailed characterization of different ABS types and a systematization regarding strategic opportunities to enrich service portfolios in practice.

Keywords: analytics-based services, archetypes, service portfolio, cluster analysis.

1 Introduction

Rapid advances in information technology threaten existing product and service portfolios, drive changes in established business strategies, but also open up new opportunities for existing and new market participants [1, 2]. In these dynamic markets, the ability to expand the existing service portfolio with new innovative services that exploit technological advances has become a key focus of organizations [3, 4].

One approach is the use of data and analytics to enable new innovative services [5–7]. Analytics-based services (ABS) are a novel type of service which encompasses the application of analytical methods (‘analytics’) to data. It aims to increase customer value by supporting the customer to make better decisions, solve more complex problems and ultimately reach their goals more effectively or efficiently [8]. For example, BASF uniquely supports farmers with ABS to increase yields [9]: Using satellite images of its customers' fields (data) and combining them with weather

15th International Conference on Wirtschaftsinformatik,
March 08-11, 2020, Potsdam, Germany

https://doi.org/10.30844/wi_2020_j7-hunke

simulations (analytics), it derives current vegetation indices to predict the risk of certain plant diseases. Farmers proactively receive field-specific fertilizer recommendations including the required dosage calculated for each field zone. Industry experts stress that ABS hold great promise for companies to enrich their service portfolio by either achieving or sustaining a competitive advantage [10] through a deeper integration in the value creation process of the customer [11] or by exploiting entirely new markets [12].

Despite the research focus that the topic has received in the academic literature [13], it remains unclear how organizations can systematically exploit data and analytics to expand their service portfolio [14]. Recent research suggests that a systematization of opportunities provides insights into immature research topics. For instance, Remane et al. [15] derive types of car sharing business models to shed light on the systematic discovery of car sharing opportunities for organizations while Gimpel et al. [16] derive types of FinTech start-ups to provide insights on how they leverage digital technologies to offer innovative financial services. Thus, systematizing with the help of dedicated service types seems a promising approach to provide organizations with actionable insights that could pave the way for new value creation opportunities in the context of ABS.

The objective of this study is *to provide a systematization of ABS by revealing different ABS-types*. Thus, this paper addresses the following research question: *What are archetypes of analytics-based services that can be found in the market?*

For that purpose, we apply archetype theory [17] to our study context to identify archetypes of ABS, i.e. theoretical prototypes or modular service configurations that provide a systematic perspective on the different possibilities to create customer value with data and analytics [17, 18]. For the analysis, we build upon ABS offered by start-ups, since start-ups are often referred to as pioneers by taking advantage of new technology-enabled opportunities in their service offerings [19]. We use an existing taxonomy of ABS providing their common components to classify a dataset of 105 real-world ABS offered by start-ups. Afterwards, we perform a cluster analysis following the established procedure suggested by Puni and Stewart [20] to identify different clusters, i.e. groups of ABS-cases that share similar characteristics. We interpret the resulting clusters to derive four different archetypes of ABS. Based on these results, we consolidate the four ABS-archetypes into a strategic framework to discuss possible pathways for organizations to establish ABS.

Our work contributes to the emerging discourse of ABS by specifying dedicated types of ABS including their respective characteristics which lay the foundation for a more profound conceptualization of this new type of service in future research. Additionally, practitioners benefit from our discussion as we disclose possible strategies for establishing ABS in the market and, therefore, respond to management issues reported in the field of ABS [7, 14].

The paper is structured as follows. Section 2 provides an overview of the extant literature our research builds upon. We subsequently lay out our detailed research design in section 3, followed by the resulting findings in section 4. We discuss our findings and implications, reflect limitations and propose opportunities for future research in section 5, before we conclude our research.

https://doi.org/10.30844/wi_2020_j7-hunke

2 Related Work

The aim of this paper is to identify ABS archetypes to provide a systematic differentiation of possible business opportunities. Thus, two topics from the literature are relevant to build our research upon. First, we present prior research that contributes to the conceptualization of the use and exploitation of data and analytics in services. Second, research investigating the classification and systematization of services in general offers a promising basis for our research.

2.1 Analytics-Based Services

The continuously increasing amount of data, combined with advanced analytics technologies are considered to have great potential to expand the organizations' business portfolio by opening up opportunities to create new service offerings [10, 13, 21, 22].

Chen et al. emphasize two general practices to create new services, Data-as-a-Service (DaaS) and Analytics-as-a-Service (AaaS) [23]. Firstly, DaaS focuses on providing raw and aggregated content while, secondly, AaaS provides customers with a wide range of customizable analytical methods that enables them to analyze large amounts of data. These practices can be offered independently or in combination in entirely new stand-alone data-driven service solutions [24].

Apart from that, data and analytics also enable the creation of added value in combination with existing products or services. This can be achieved by providing additional information-intensive services for the customer to enrich the value proposition of existing services [25, 26]. Smart, connected products can be amplified based on e.g. sensor data they generate. Smart services "wrap" meaningful product-related insights around them based on that data to enrich the value that is offered by the core product [27–29].

In this still emerging field of research that investigates the use of data and analytics for new service offerings, the terminology still varies (e.g., "smart services" [27], "data-driven services" [24], "information-intensive services" [25], "data-wrapping" [28]). The use of (sophisticated) analytics is acknowledged to play a key role in creating value from data [30]. However, despite different conceptualizations proposed in the field, it still needs to be further investigated how data and different kind of analytics can be systematically combined to contribute to value in new service offerings. We refer to services which encompass the application of analytics to data in order to create customer value in new services – either as a stand-alone solution or bundled with existing products or services – as *analytics-based services*.

2.2 Systematization of Analytics-Based Services

Systematization approaches, such as taxonomy development or archetype identification, are an essential instrument for tapping into new fields of research. They contribute to structuring pre-existing research, facilitate the positioning of new contributions and, thus, support a profound theory-building process in a still

https://doi.org/10.30844/wi_2020_j7-hunke

underdeveloped field of research [31, 32]. IS research has adopted this approach in order to identify (managerially) useful generalizations and recommendations for research and practice, e.g. to better understand and manage the different types of relationships between companies and their customers afforded by services [33].

Identifying service archetypes representing generic, theoretical prototypes or modular service configurations serves research with the description of key elements of services and identifies possible strategies for realizing service-business opportunities in practice [17, 32]. Allmendinger and Lombreglia suggest four archetypes of smart services to provide a more systematic view on business opportunities to enrich existing products [34]. Similar, several authors strive to systemize the manifold opportunities that digitalization, respectively the data generated in its context, offers by proposing archetypes to more systematically manage transformation processes in practice [35, 36].

Current systematization approaches still focus on very specific contexts or neglect the key role of analytics for the service. Hartmann et al. [24] unveil completely new ways to conduct business solely based on data as a key resource and introduce six types of data-driven services. By differentiating the identified service types according to the underlying data source, and according to the type of performed activity, they provide a basis for understanding how companies can develop completely new data-driven services that provide value. Rizk et al. [37] developed a systematization of data-driven digital services to better understand their key elements consisting of data collection mechanisms, data utilization, insights usage, and service interaction characteristics. Applied to real-world use cases, they found that services that are based on data are either used as encapsulated services in larger service systems, as data visualizers, or as specialized recommenders. Thus, the emerging research field of ABS would benefit from a more general systematization of ABS unveiling different ABS types to further deepen the understanding of how data and analytics can be leveraged to create new service offerings systematically.

3 Research Design

In this study we combine quantitative and qualitative research [38]. In the quantitative phase, we use an existing taxonomy of ABS to classify a number of real-world ABS cases from start-ups and group them using cluster analysis. In the qualitative phase, we interpret the identified clusters to derive ABS archetypes. In this section, we focus on the explanation of the data collection and analysis process for the quantitative analysis. Details on the derived archetypes are provided in the results section.

3.1 Data Collection

This paper aims to derive archetypes of ABS – new, innovative services that provide customers with new value based on data and analytics. For this purpose, we base our analyses exclusively on ABS offered by start-ups. Start-ups tend to be the first to exploit the opportunities of new technologies for their business [19] and, unlike large

https://doi.org/10.30844/wi_2020_j7-hunke

organizations, start-ups often offer a single, clearly defined service. Therefore, building on ABS from start-ups as a unit of analysis seems to be adequate for our investigation.

To identify ABS cases, we drew upon AngelList's database, an online platform that enables start-ups to raise money and investors to invest in attractive business concepts. For this purpose, start-ups can advertise their projects via profiles on the platform and, thus, publish information about their company and their proposal. In addition, the companies self-categorize in the database by specifying their thematic focal points with the help of keywords.

In the first step of our collection process, we examined the available keywords and selected those that could be thematically linked to ABS. We then collected all start-up cases that were related to the identified keywords, namely “analytics”, “machine learning”, “artificial intelligence”, “data mining”, “big data”, “deep learning”, “internet of things”. By collecting all cases in the first step, we aimed to eliminate researchers’ selection bias [39]. Second, we reviewed the identified cases to see whether they actually described ABS. To this end, we examined whether data and analytics were described in the service description as a key aspect to create value for B2B or B2C customers. After removing duplicates, this filtering resulted in a final set of 2472 cases identified as ABS.

In order to obtain a manageable dataset for the subsequent coding phase, we randomly selected 15 use cases for each keyword, which resulted in a final set of 105 ABS cases consisting of the descriptions provided by the start-ups on AngelList. To expand this database with deeper and insightful information about the selected ABS – as we found that the level of detail of these descriptions varied enormously – additional information about the ABS was collected in each case from the start-up's own website. This included detailed information about the functioning of their ABS, but also information about the start-up’s evolution, insights and beliefs that they had developed over time.

3.2 Coding Mechanism

Our resulting dataset consisted of textual descriptions of real-word ABS. Literature provides a rich collection of possible coding mechanisms for textual case analysis. A provisional coding approach may be used in case there exists a conceptual framework to serve as an underlying basis of a research inquiry [39, 40]. For that purpose, we built on research previously conducted to conceptualize the nature of ABS which introduced a taxonomy identifying commonly shared characteristics of this service type [8]. Taxonomies are a well-established instrument to describe and analyze new phenomena using a unified classification schema [31]. Thus, the ABS-conceptualization defined in this taxonomy served as a codebook for coding each of the 105 ABS use cases. It consists of six dimensions (cf. Figure 1); each is represented by a distinct set of generic characteristics. A detailed description of its six dimensions and their respective characteristics which are perceived as key to conceptually describing ABS can be found in [8].

https://doi.org/10.30844/wi_2020_j7-hunke

The coding of the ABS use cases was performed by a single author. To ensure validity of the conducted coding, a random 10% sample of our dataset was individually coded by a second author in an ex-post quality check. A resulting inter-coder agreement of 88.3% as percentage agreement and 73.1% as Cohen's Kappa [41] suggests an adequate coding quality. Following Landis and Koch [42], a Kappa between 61% and 80% indicates a "substantial" strength of the agreement among the coders.

Dimension	**Characteristics**				
Data Generator	Customer	Non-customer	Process	Objects	
Data Origin	Internal	External			
Data Target	Customer	Non-customer	Process	Objects	Environment
Analytics Type	Descriptive	Diagnostic	Predictive	Prescriptive	
Portfolio Integration	Stand-alone solution	Wrapped around product	Wrapped around service		
Service User Role	Recipient	Provider	Interactor		

Figure 1. Taxonomy of ABS serving as a codebook.

3.3 Cluster Analysis

Archetypes represent basic patterns from which individual copies can emerge [17]. Cluster analysis is a promising approach for identifying such archetypes. It is a statistical technique to group similar objects according to their properties aiming to achieve high homogeneity within each cluster and high heterogeneity between objects of different clusters [43].

We followed the two-step procedure suggested by Punj and Stewart [20]. In the first step, agglomerative hierarchical clustering was performed using Ward's method [44]. Agglomerative hierarchical clustering algorithms do not require a predefined number of clusters, but generate solutions for all possible cluster numbers by gradually merging the two nearest clusters in each step [43]. In order to determine the distance between the individual objects, we dichotomized our data set, i.e. each taxonomy-characteristic was represented with "1", if the characteristic was identified in the respective use case by the previous coding and a "0", if not. To measure the distance, we used the simple matching coefficient [45], since its interpretation for binary variables well fits our context. Since cluster analysis does not provide guidance in determining the number of clusters, this preliminary analysis step helped us to obtain a first approximation of a solution examining the results in a dendrogram. It allowed us to determine a candidate number of clusters and provided the opportunity to detect outliers for which cluster analysis is sensitive. In our case, four or five clusters were perceived to provide the most comprehensive insights.

In the second step, we performed an iterative partitioning clustering using the k-medoids algorithm. The k-medoids algorithm groups objects into a predefined number of clusters (*k*) by minimizing the distance between each individual object and its

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corresponding cluster-representative object (*medoid*) for all objects in a cluster [43]. Since it uses objects from the dataset as medoids, it was selected over the more common k-means algorithm making the results more meaningful for an archetypal interpretation. Subsequently, we validated the cluster solution using the silhouette coefficient [46]. A solution with four distinct cluster turned out to be the stronger solution with a silhouette value of 0.41 indicating a weak, yet existing clustering structure in our dataset [47]. For social science data such as ours, this is a typical result, as such data rarely exhibits strong natural groups [32].

4 Four Archetypes of Analytics-Based Services

The cluster analysis identified four different clusters, consisting of 24 to 28 cases. Each cluster exhibits different centers along the characteristics of the ABS taxonomy. To derive generic archetypes from our cluster solution, we followed Hembrick's [32] recommendation and inspected the characteristics' frequency distributions of each cluster to identify the most pronounced characteristics that could serve as archetype boundaries. The resulting cross table provides an overview of the frequency distribution of characteristics for each archetype (cf. Table 1). In the following, we provide a detailed description for each archetype by highlighting typical characteristics and providing an illustrative example.

Archetype A: Making data useful to customers. The first cluster characterizes ABS that aim to make existing data sources useful to their customers. While these customers oftentimes are aware of or might have access to large amounts of data in their business context, data in its raw form exhibits a limited applicability to them. Thus, this ABS-type processes data in ways so that customers can access it and use it more easily in their daily activities. Typical applications in this cluster constitute aggregated reports, dashboards, or APIs which provide customers with the opportunity to make better decisions based on data.
Typical for this type of ABS is the use of process data (93%), e.g., business KPIs or production data, which is generated by the ABS customers (external, 100%). Other examples for an external origin are data collected from publicly available sources. The data is processed using descriptive analytics (100%) to aggregate or visualize insightful information targeting these processes (96%). Thus, the customer predominantly engages with the ABS by providing the service-relevant data (68%) – in case the data originates from publicly available sources, the customer merely receives the aggregated information without any further engagement with the ABS (29%).

One example for a start-up offering this ABS-type is *Rollbar*. *Rollbar* provides a real-time error reporting system and continuous deployment monitoring for software development teams. By integrating *Rollbar* into the customer's local development architecture, it collects all tickets that are created for detected errors. This data – which, potentially, is available independently from *Rollbar* – is aggregated and visualized in a real-time dashboard. Additionally, it automatically links subsequent

https://doi.org/10.30844/wi_2020_j7-hunke

bug reports to the respective ticket and calculates the correlation of errors with previous occurrences. Providing aggregated information team leaders can build on, the service allows to capture errors earlier during development and, thus, creates value for them by improving their software delivery processes across the entire development lifecycle.

Table 1. Results of cross table analysis.

Dimension	Characteristic	Archetype			
		A	B	C	D
Number of cases per cluster		*28*	*26*	*27*	*24*
Data Generator	Customer	14%	65%	37%	0%
	Non-Customer	0%	4%	4%	0%
	Processes	93%	69%	93%	17%
	Objects	14%	23%	22%	100%
Data Origin	Internal	0%	12%	19%	92%
	External	100%	96%	85%	8%
Data Target	Customer	4%	96%	59%	17%
	Non-Customer	0%	12%	4%	0%
	Processes	96%	27%	41%	33%
	Objects	14%	0%	11%	63%
	Environment	4%	0%	0%	33%
Analytics Type	Descriptive	100%	35%	7%	21%
	Diagnostic	0%	65%	4%	13%
	Predictive	0%	0%	67%	58%
	Prescriptive	0%	0%	22%	8%
Portfolio Integration	Stand-alone	100%	96%	96%	4%
	Wrapped around product	0%	0%	0%	96%
	Wrapped around service	0%	4%	4%	0%
Service User Role	Recipient	29%	8%	4%	17%
	Provider	68%	88%	0%	4%
	Interactor	4%	4%	96%	79%

20% – 50% 51% – 80% 81% – 100%

Archetype B: Delivering Data-Based Insights. The second cluster describes ABS that aim to create new value by delivering meaningful insights to their customers based on data. In contrast to the previous archetype which aims at enabling customers to use data on their own behalf, this archetype also "digests" the data for the customer. It uses more sophisticated, diagnostic analytics to deliver actionable insights customers can apply, e.g. to make more informed decision. Typical applications in this cluster comprise targeted benchmarks or meaningful alerts.

ABS in this cluster use data that is generated by dedicated business processes (69%) or data that is generated elsewhere by the customer (69%) – thus it originates externally (96%). The data is predominantly analyzed to identify individual insights about customers (96%) using diagnostic analytics (65%), i.e. it is not only identified *whether* something happened, but also delivers insights *why* something happened. Similar to the previous archetype, the customer mainly engages in the ABS by providing the relevant data (88%).

UBiome provides a health care ABS that allows customers to understand their microbiome with the ultimate goal to improve their lifestyle. *UBiome* provides a self-sample kit, which their customers use at home. The sample is sent to *UBiome,* where it is analyzed using advanced statistical techniques. A personalized diagnosis report is prepared comparing the results with a healthy reference range and individual insights are provided on which the customer can improve his everyday life, e.g., via healthier nutrition.

Archetype C: Providing Data-Based Recommendations. The third cluster describes ABS that aim to provide customers with meaningful, contextual recommendations for action to solve problems. Business value is really unlocked from data when critical insights are gained followed by immediate actions applying that new knowledge. To this end, this type of ABS processes data in a way that allows to predict possible outcomes and to make recommendations to the customer inspiring immediate action and influence the customer's decisions.

Typical for this type of ABS is the use of process data (93%) which is occasionally enriched with customer-generated data (37%). The data mainly originates externally (85%). However, in this cluster start-ups also start using own, internal data (19%) such as self-built machine learning models or relevant self-collected data. This ABS-type is primarily intended to derive customer-specific, i.e. individually tailored insights (59%). Distinctive for this cluster also is the use of advanced analytics using predictive (67%) or prescriptive methods (22%) to derive the required insights. The results suggest that the recommendations provided by the ABS are highly tailored to the customers' individual needs. To achieve this, this type of ABS requires a deep integration and high interaction with the customer (96%).

One example for a start-up offering this ABS-type is *Proximus*. *Proximus* uses advanced machine learning models to analyze consumer behavior in brick and mortar stores. They identify popular product dependencies among consumers and predict future revenue streams on a daily basis to recommend better store layouts or product bundles. Highly engaging with their customers via an online platform, *Proximus'* recommendations inspire immediate actions for decision-makers that lead to higher sales on a single-store level.

Archetype D: Enabling Novel Ways to Conduct Business. The fourth cluster describes ABS that aim to create new value by enabling truly new ways to conduct business for their customers. For that purpose, this ABS-type creates, in contrast to the previous archetypes, completely new data sources that contain customer-specific information. Thereby, this type of ABS creates new opportunities to identify

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meaningful insights and to make purposeful recommendations for their customers. Typical approaches for this archetype are sensor based IoT objects that are integrated into the customer's workflow to deliver new data, insights, and ultimately provide ground for improved ways to conduct business.

Typical for this type of ABS is the use data generated by objects, e.g., sensor data (100%). Thus, these services draw upon their own, internal data (92%). The data is analyzed with regard to the object's own condition and state (63%) or to the customer's general business processes (33%). These insights are derived predominantly using predictive analytics (58%). Similar to archetype C, these services use customer-related data sources resulting from deep customer interaction (79%).

Skycatch is an example for a start-up offering this type of ABS. *Skycatch* provides its customers, construction management firms, with a self-developed drone, which allows them to digitize large construction sites using 3D-mapping technology. *Skycatch* seamlessly integrates this data, which is continuously updated, e.g., on a daily basis, into the customers own data models using a cohesive data suit. This integration allows their customers to renew existing workflows, reaching previously unattainable gains and efficiencies, e.g., by controlling contractors' billing for removing dirt through calculating the dirt volume based on 3D image.

5 Discussion and Implications

Using data and analytics in service offerings as a means to create new customer value has recently become a much-regarded strategy by organizations [3, 10] and is being actively explored by academics [7, 13]. Yet, little is known about how organizations can leverage data and analytics to systematically expand their service portfolio. To this end, this research identifies four archetypes of ABS that shed light on the objectives market-pioneers pursue when offering such services creating novel value for their customers. That is, 1) *making data useful to customers*, 2) *delivering data-based insights*, 3) *providing data-based recommendations*, and 4) *enabling novel ways to conduct business*. Each archetype is described by a set of distinct characteristics that unveils the unique interplay of data, analytics, and customer integration of each type.

In order to contribute to systemizing the field of ABS and to develop an understanding of how these four archetypes relate to each other, we developed a strategy positioning map on two key dimensions. Rust and Huang [48], amongst others, describe how services are able to evolve over time. Service offerings expand from static "selling services" to interactive "co-creating services" as the relationship between the service provider and the customer becomes stronger over time. Building on that, we define a "transactional–relational" axis to capture the degree to which a continuing, stronger relationship is maintained and the ABS is deeper embedded in the customer's own systems and working habits. In addition, we noted that our results suggested a tendency towards a steady transition from external to internal data sources that were used in the different archetypes. We define a second axis,

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“common–unique”, which captures the degree of uniqueness of the data used in the ABS.

Figure 2 shows the position of the four archetypes using these two dimensions in the strategy positioning map. Archetype A is based on common data and a rather static customer interaction, as the service-relevant data is also easily applicable for potential competitors and the actual value is created downstream by the customer. In archetype B, the interaction with the customer is more pronounced since the service is more tailored to the individual customer and the service provider more strongly contributes in the value creation process [49]. This results in the application of more demanding analytics in the service. Archetype C is characterized by a strong, continuous and interactive customer relationship, as the service is deeply embedded in the customer's own processes. While customer-provided data could, potentially, also be applied by competitors, type C integrates own data and experiences to create individual, more meaningful recommendations increasing the uniqueness of the underlying database for the service. Archetype D resembles similar relational characteristics compared to type C. Yet, archetype D strongly builds on new, self-generated data sources resulting in a high uniqueness of the data. Both, archetype C and D rely on sophisticated, predictive analytics to reach the intended service objective.

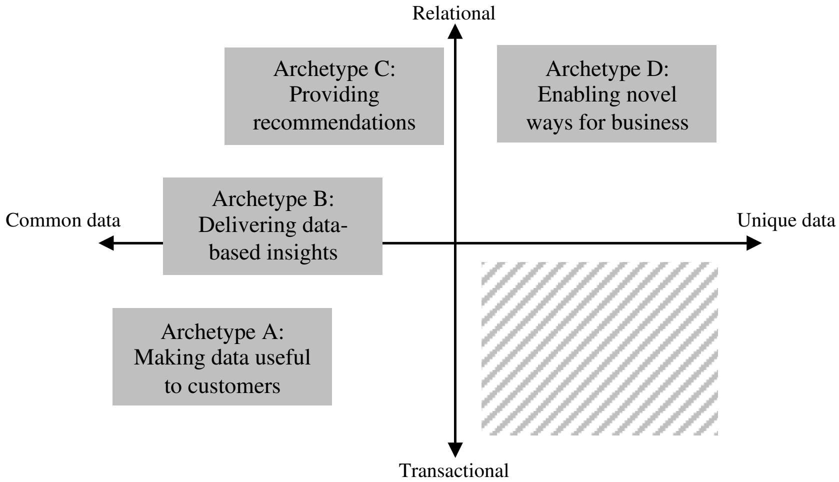

Figure 2. Strategy positioning map of ABS archetypes.

Our analysis did not reveal a single ABS creating unique data that would build on a transactional customer relationship to make that data simply more accessible to customers (hatched area in Figure 2) – suggesting that this area should be avoided since the customer value seems to remain limited. Instead, we noticed a number of ABS in our sample that had previously taken an “evolutionary” pathway along both axes by intensifying customer interaction and advancing analytics sophistication over time. *Shoppermotion*, for instance, offers in-store analytics for the retail and consumer industry. Using beacons attached to shopping cards transmitting their store location, *Shoppermotion* is able to provide stores with highly individualized, real-time recommendations to leverage in-store consumer behavior (type D). Before using sensor-based, self-generated data, *Shoppermotion* relied solely on customer-generated in-store cash system data to provide recommendations (type C). In the very beginning, the company simply aimed to reveal insights from past-sales data (type B).

5.1 Implications for Research and Practice

This study offers a number of *theoretical implications* that contribute to a deeper understanding of ABS. Using an exploratory and descriptive analysis, this research identifies four archetypes of ABS and introduces a framework to identify possible strategies to expand service portfolios with ABS – a systematization of ABS that was missing so far. The findings provide a possible reference point for further studies aiming to theorize how analytics applied to data can be of real use for customer-facing business practices; thereby providing a basis to tap into this, so far, blind spot in IS literature [50].

This study also offers a number of *managerial implications* that can be particularly helpful for organizations that are already taking advantage of ABS to create new customer value or are planning to do so. First, our quantitative analysis revealed typical approaches for using ABS to expand the service portfolio. This overview may help to establish a more informed and systematic development of strategies to use data and analytics in service offerings, in general. Second, each identified type of ABS is described with the purpose of revealing commonalities and key components. This might provide a valuable orientation for organizations when investing in ABS initiatives, e.g. as possible blueprints for developing new services or guidelines for transforming existing ABS into more sophisticated ones.

5.2 Limitations and Future Research

Our research certainly comes with some *limitations*. First, our analysis solely builds on start-up use cases. While we argue that start-ups are a purposeful source to identify ABS offerings, this decision limits the generalizability of our results regarding larger organizations. Second, our data collection approach is limited to the AngelList database and, therefore, this choice might influence the results' generalizability. We were only able to consider ABS by start-ups that tout for investors on this platform, increasing the chance to miss innovative ABS elsewhere. Third, the data sample size in this study was limited to 105 use cases due to the significant amount of manual work required to code each case. While this reflects the exploratory nature of our research, this decision potentially limits the ability to identify more nuanced differences between use cases using cluster analysis.

These limitations at the same time leave the potential for *future research*. First, the analyses should be conducted again using a larger sample of cases, ideally including ABS use cases from larger organizations to increase the data sample's diversity. Second, future research could deeper investigate causal effects of ABS-enriched service portfolios. For instance, it would be interesting to investigate the

https://doi.org/10.30844/wi_2020_j7-hunke

organization's different business capabilities required depending on the archetype they intend to offer. As we already pointed out, the skillset regarding analytics capabilities seems to vary between the archetypes, making it a fruitful topic to start with. Third, we see the monetization of ABS as a promising field for future research. Interestingly, we found that organizations that had evolved, e.g., from archetype A to archetype B, usually kept their initial service offering and used it as a "basic service", often in combination with a freemium revenue model to attract possible customers. Thus, future research might investigate how revenue models look like for different ABS archetypes.

6 Conclusion

With the digital transformation gaining momentum, organizations increasingly explore how to expand their existing service portfolio using ABS. Yet, conceptual knowledge on this novel service-type remains limited and IS literature misses to provide actionable insights how such a portfolio enrichment can be achieved in a systematic way. Building on a data sample of 105 ABS use cases that are offered by start-ups in the market and using an established clustering procedure, we derive four distinct types of ABS archetypes that provide initial empirically grounded evidence how ABS create new customer value. These archetypes suggest that organizations may enrich their existing service portfolio using ABS by either 1) *making data useful to customers*, 2) *delivering data-based insights*, 3) *providing data-based recommendations*, or 4) *enabling novel ways to conduct business*.

The findings in this research shed light on how ABS create customer value based on data and analytics using an archetypal systematization. We believe, this systematization contributes to conceptualizing ABS in this young research field and helps researchers to channel future ABS-related theorizing attempts. Additionally, we believe practitioners benefit from our discussion on how the identified archetypes might be strategically distinguished. We introduce a strategy positioning map to propose different opportunities to enrich the service portfolio providing a helpful starting point for ABS initiatives in practice.

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