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Expanding Frontiers of Customer Knowledge Management to Sustain Competitive Advantage: The Mediating Role of Predictive Analytics

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Abstract

Business reality, as well as IT literature, is indicating the shift towards data-driven societies. However, business research is lacking the conceptualizations and explanations in this regard. The common denominator of these perspectives is the key role of customer integration. This can be ensured by efficient managing of customer knowledge. At the same time, online activity of companies provides a possibility to generate customer behavioral data, which potential can be unveiled using specific techniques and tools, such as predictive analytics. Given the peculiarity of such knowledge assets, generated via analytics, it has to be specifically addressed within customer knowledge management. Using resource-based view as a theoretical lens, this study first deduces research propositions which then analyses against the empirical findings from case studies. Findings indicated specific nature of analytics-generated customer knowledge that challenges the frontiers of customer knowledge management towards integration with data management and information management.

Keywords: Customer Knowledge, Predictive Analytics, Customer Knowledge Management, Data, Resource, Case Study

1. Introduction

Technological development is driving new ways of customer integration, bringing the role of customer knowledge to a new level. The respective topic draws more attention in the context of social media and communities of practice, including online platforms (Wu and Fang, 2010; Fuller and Matzler, 2007; Sawhney *et al.* 2005). An underlying technology enables companies to generate a vast amount of customer behavioral data, which is regarded as Big Data (Koen *et al.* 2001).

Big Data are among the mostly debated topic nowadays. However, despite the significant contribution for the business, the research in this area predominately resides at the technology side (Bughin *et al.* 2013). Business reality is already filled with undeniable effects of Big Data implications on companies' performance. Data, per se, has no or little value; yet, it is a granulated presentation of knowledge that should be discovered. This need fuels the whole wave in development of respective tools, techniques and strategies to convert data into specific and accurate insights (Chase, 2014). In this vein, the concept of Big Data analytics - an umbrella term for the processes of processing and analyzing data - has emerged and continues evolving towards retrieving more insights and value from data (Chen *et al.* 2012).

Technological advances challenge the nature of knowledge management, pushing it towards addressing e-business reality (Borges Tiago *et al.* 2007; Plessis and Boon, 2004). These, in their turn, pose the changes to customer knowledge management (Lopez-Nicolas and Molina-Castillo, 2008). IT developments provide extensive opportunities to optimize and increase efficiencies of knowledge management processes (Ofek and Sarvary, 2001). The importance of managing customer knowledge - through technological possibilities of managing behavioral data - was already observed in various industries and sectors (Chua and Banerjee, 2013; Gamble *et al.* 2001; Lopez-Nicolas and Molina-Castillo, 2008). Yet, the literature on knowledge management does not acknowledge the changing nature of knowledge as a strategic asset (Rowley, 2006) in the scope of technological development. However, the sources of knowledge creation which enabled by technological development opens new horizons in this domain. Despite the still ongoing trend in separating knowledge management from information and data management, the reality constantly fuels the synergies of these. The main challenge is hidden in the process of customer involvement, as it comprises an information flow and generation of behavioral customer knowledge. The complexity of managing the data is assumed to be tackled by predictive analytics. This study offers the first understanding of this issue. In this vein, the research purpose of this study is to observe how technological advances affect the nature of customer knowledge management; what are the peculiarity of analytics-driven customer knowledge assets; and how customer knowledge management helps to sustain competitive advantage.

To address the aforementioned research problem, this research applies a Resource-based View (RbV) logic (Barney, 1991), specifically the asset stocks and flows theoretical foundation by Dierickx and Cool (1989), as a theoretical lens. The respective theoretical premises are used to address the new type of customer knowledge, which is generated by analytics techniques, to see whether the given theories are still adequate for embracing changes caused by technological advances. Theoretically deduced research propositions are to be empirical analyzed to draw conclusions regarding the customer knowledge management and analytic knowledge as a resource for sustaining a competitive advantage.

The paper is structured as following: first, introduction of the concepts customer knowledge management and predictive analytics, followed by the introduction of asset stock and asset flows theoretical foundations and development of respective research propositions (RP); second, methodological considerations; third, empirical observation and analysis of RPs; forth, summarizing discussion of findings and conclusion.

2. Theoretical Background

2.1. State of Customer Knowledge Management

The research in the field has been striving to crystallize the concept of customer knowledge management (CKM) out of the debate on knowledge management (KM) and customer relationship management (CRM) (Attafar *et al.* 2013; Bueren *et al.* 2004; Gebert *et al.* 2002; Jarvenpaa and Eerikki, 2002). The emergence of CKM, in this vein, was determined by the paradigm shift towards the customer-centric approach (Chua and Banerjee, 2013). Thus, CKM aims to *"[...] capture, organize, and share, transfer and control knowledge related to customers for organizational benefits"* (Chua and Banerjee, 2013, p. 238).

The characteristics of customer knowledge - as well as knowledge, in general - differ by their nature, what results in its different subtypes. Customer knowledge differs according to its sources and was categorized by Gebert *et al.* (2003) as: (1) knowledge for customers which refers to knowledge as know-how of the product, industry, operations and market, which are important to satisfy customer needs; (2) knowledge about customers includes the knowledge of a customer profile, behavioral motivation, purchasing activities, priorities etc. The knowledge is crucial to identify, define and target the most valuable customers; (3) knowledge from customers presents tacit knowledge which resides at the customer site, including the knowledge and experience about certain product (and company) and competitor.

Various researchers tend to assign different values to the aforementioned types of knowledge flows, stating the greater importance of the knowledge *for* and *from* customers, and rate it high above the knowledge *about* customers (Garcia-Murillo and Annabi, 2002; Gebert *et al.* 2002; Gibbert *et al.* 2002) or vice versa (Davenport *et al.* 2001). The latter claims the knowledge *about* customers being hidden behind the patterns in customer behavioral data within the processes of online interaction. However, behavioral data is also an articulation of tacit knowledge from customers, as their buying preferences are built upon their knowledge about other products and companies. Therefore, the clear distinction and -what's more- prioritization of knowledge value cannot and, perhaps, should not be clearly stated. Customer-centric organizations should reconfigure their CKM processes to embrace all these types of knowledge (Rowley, 2006).

Charles *et al.* (2001) claim a positive impact of data mining on customer knowledge value within the knowledge management framework at the example of shopping centers. Thus, CKM - which aims to understand how to manage customer knowledge for understanding customer needs (Roscoe, 2003) - in technology-driven context, should be able to integrate data management, information management and knowledge management (Rowley, 2006).

The processes of converting customer data to information and knowledge is already taking place within the companies (Rowley, 2006), yet some data offers little insights, e.g. sales receipts data (Lesser *et al.* 2000), what triggers companies to take a deep look for more interactive strategies of gaining an understanding of the customers in extended dialogs. However, customers might not be able to properly articulate their needs (von Hippel, 2005) or might not be willing to share their knowledge (Desouza *et al.* 2008). However, in e-business the processes of managing customer knowledge, its sources and mediators significantly differ from traditional ways of collecting customer knowledge through traditional market research (Rowley, 2002b). The online interactions foster the generation of data which indicates various customer behavior. Respective activities in the field of Big Data analysis, lack abroad scale of success and significant business improvements (Rowley, 2002a) despite the rocketing debates on the potential of Big Data (La Valle *et al.* 2011). To overcome this gap, (Rowley, 2002b) suggests that certain techniques, e.g. data mining, have a great potential of converting data into knowledge. Taking this elaboration as a starting point, we assume that predictive analytics - as an analytical tool based on data mining techniques - has a potential to unveil the hidden potential in customer behavioral data.

2.2. Predictive Analytics: Application and Potential

The Big Data and its implications becomes a new arena for sustaining competitive advantage, enabling optimization of firm performance (Bell, 2013; Bose, 2009; Sharma *et al.* 2010). While some companies show tremendous results from leveraging Big Data, others struggle to learn competing in this sphere. In the long-run, those who will not realize the role of data for decision-making, heavily jeopardize their chances for survival (Davenport, 2006). To unveil the potential of data, a set of techniques and tools are required, which are named 'analytics'. Business analytics is defined as *"[...] an integration of disparate data sources from inside and outside the enterprise that are required to answer and act on forward-looking business questions tied to key business objectives"* (Isson and Harriott, 2013, p.3). Analytics carries out the processes of knowledge discoveries to convert the data into meaningful insights regarding customer behavior and market trends, production processes, service optimization and supply chain management (Davenport and Harris, 2007; Trkman *et al.* 2010; Waller and Fawcett, 2013). Despite the extensive debate on the potential and application of analytics (Chae, 2014; Demirkan and Delen, 2013), it has a tendency to shed a light on the issue predominantly from technological perspective.

Analytics, as a technology, is constantly under the process of evolving towards a maximizing the value from data. In this vein, it evolved from just summarizing historical data and answering the question *'what happened?'* towards more proactive approach on data utilization. Thus, advanced analytics embraces the limitation of descriptive analytics to address the question *'why some specific event happens and what can we learn from it?'* (Davenport, 2006;

La Valle *et al.* 2011). Siegel (2013, p.11) defines predictive (advanced) analytics as a *"[...] technology that learns from experience (data) to predict the future behavior of individuals in order to drive better decisions"*.

A wide range of companies have already paved the way towards benefiting from data through implementation of predictive analytics. PA proved its potential in the areas of finance, marketing, production, HR management, as well as, healthcare and public sector (Siegel, 2013). Big Data analytics had a great impact on retail, providing sellers with a range of information on customer preferences to predict their buying behavior (Srinivasan, 2012). This is particularly beneficial for retail e-commerce – companies which have no chance for physical interaction with customers to understand their needs.

Scrutiny indicated that potential of PA is addressed in the general scope of decision-making processes, implicitly integrating the role of customer knowledge management. The number of managerial reports illuminates the potential of advanced analytics, referring to specific improvements in KPI. Yet, explicitly and specifically these issues were not addressed, in particular in academia. Thus, this study explores the role and underlying processes behind the customer knowledge, generated using PA, in sustaining competitive advantage.

2.3. Customer Knowledge as a Strategic Asset: A Resource-based View

Seeking to discover the sources of sustaining firm's competitive advantage, (Barney, 1991) identified the characteristics of the resources which ensure unique competitive position. In this vein, a resource-based view (RbV) fundamental logic lies upon the role of idiosyncratic and inimitable resources for the firm competitiveness (Barney, 2001; Peteraf, 1993). Thus, only valuable, rare, imperfectly imitable and non-substitutable resources - regarded as strategic assets (Meso and Smith, 2000) - are the sources of firm's competitive advantage. While data is just a commodity, customer knowledge cannot be easily copied (Lesser *et al.* 2000), which is a contributor to its competitive advantage (Bollinger and Smith, 2001).

To sustain competitive advantage by impeding imitation of valuable resources, Dierickx and Cool (1989) claim that only accumulation of certain assets would ensure this process. Building upon Barney's theory of factor markets (Barney, 1986), the respective assets could only be accumulated, as many assets are non-tradable (Wernerfelt, 1989). Given this argumentation, assets are accumulated by coupling specific asset flows at any point of time.

PA, being a unique technology of discovering knowledge from data, could have a potential to secure companies competitive advantage by contributing to asset stock accumulation. To shed light on the relationship between data, customer knowledge, as a resource, and competitive advantage, we look at these relationships through the prism of the characteristics of the processes of asset stock accumulation, developed by Dierickx and Cool (1989):

Time compression diseconomies -*resources, accumulated over a longer time period through incremental improvements, are more difficult to imitate.*

Knowledge management should deviate from solely managing internal knowledge sources and move towards sustaining competitive advantage on a broad scale (Tallman *et al.* 2004). Integration of knowledge management with technological aspect in the context of customer involvement challenges the role of knowledge as a strategic resource (Halawi *et al.* 2005).

Current market realities limit the potential of single market research, which is usually conducted annually or even more rarely. To embrace market dynamics, the need to address customers' needs on a constant basis, to recognize behavioral patterns, becomes more vivid. Recognition of underlying market trends rests on the ability to manage customer knowledge in consistent manner. In this vein, time becomes an important dimension for corporate decision-making, to ensure the flexibility of response to market needs (Sawhney *et al.* 2005). Companies with dominant online presence generate customer data of great volume and complexity, searching for the ways to embrace these challenges.

Given the volume of transactions and services online, the current technological advances enable comprehensive possibilities to collect and benefit from almost all kinds of behavioral data, referred as Big Data. However, data, per se, does not pose any significant value for the company unless it is being properly processed, analyzed and utilized. This debate addresses analytics as a complex form of data utilization. Analytics, as any other type of technological tool, is constantly in the process of improvement. It evolved from single reporting to complex and advanced techniques of data analysis. The recent generation, known as advanced or predictive analytics, does not only unveil hidden behavioral patterns of individual customers but makes a comprehensive assumptions of how a certain customer will react in a specific case. This knowledge is a tremendous input for e-businesses (Rowlay, 2006). Thus, PA that rests on data mining principles provides possibilities to build a consistent and coherent foundation to understanding market fluctuations. The unique insights, a firm receives from data, prevent imitation of customer knowledge stocks for understanding market trends which yield sustaining competitive advantage.

Knowledge utilization is significantly affected by the time dimension. Knowledge stock accumulation is determined by the consistency and continuity of asset flows. If some asset accumulations could be achieved by intensive input of certain resources (e.g. speed up R&D projects by extensive financial injections), the ‘time-money’ trade-off is significantly limited in case of accumulation of knowledge as an asset. Dierickx and Cool (1989) claim that longer period of resource accumulation prevent their imitability. Transferring this logic to the context of generating customer knowledge from data, the before discussed imitability of knowledge as a resource could be achieved by generating data over long periods of time which rest on the age of the company. Given the argumentation above, the following research proposition will be deduced:

RP1: Older firms have higher potential of analytical knowledge accumulation, and thustend to obtain more favorable conditions for sustaining competitive advantages.

Asset mass efficiencies - *accumulated initial asset stocks facilitate further assets accumulation.*

Companies, whose business model is dominated by online activities, manage their knowledge assets with a close connection to data. In this context, Rowley (2002b, 2006) claims that such companies can, and should benefit from different sources of customer input generated online. Looking at the customer input from the perspective of data science, maximization of data utilization efficiencies can be achieved under the conditions of continuous and consistent data flows (Nisbet *et al.* 2009). It is critical as the nature of data mining techniques is a foundation of data utilization processes. Continuous learning from the data and thus, continuous customer involvement and the identification of needs of individual customers are benefiting from significant volumes of data. Yet the quality of data is not a subject of compromise in any case, otherwise any tools or comprehensive algorithms will generate unreliable results (Nisbet *et al.* 2009).

The advantages of building volumes of asset stocks are regarded by Dierickx and Cool (1989) as asset mass efficiencies. Only accumulation of certain masses of asset stocks ensures greater accumulation of assets further. Applying this perspective to customer knowledge management, to sustain competitive advantage and prevent imitation of knowledge assets, companies should generate customer knowledge assets structurally, in great variety and over significant periods of time. The challenges of data extrapolation are typical for processes of customer knowledge accumulation, especially in consumer markets (Lopez-Nicolas and Molina-Castillo, 2008). However, building a sustainable database which could be considered as a knowledge-based asset stock demands specific applications.

The importance of achieving asset mass efficiencies triggers the utilization of appropriate techniques. Given the peculiarities of the entire knowledge discovery processes which underlie customer involvement by accumulating knowledge-based assets on customer behavior, predictive analytics offers a promising technological possibility to achieve asset mass efficiencies. It has a potential to facilitate stock accumulation by maintaining consistency and continuity of asset flows. For that reason, we developed research proposition 2 as the following:

RP 2: The more data a company generates, the more analytical customer knowledge it generates, and thus the easier it is to sustain a competitive advantage.

Asset erosion - *asset stocks have a tendency to depreciate.*

In fact, customer knowledge assets have a very vague accumulation rate as customer behavior changes daily and may cause information ambiguity. The customer needs recognition, based on data, becomes challenging unless it is based on models capable to grasp the rapid environmental dynamics. Customer knowledge management should be able to embrace this challenge in a consistent manner. However, building customer knowledge asset stock based on online interaction, is characterized by the accumulation of data which itself has a tendency to depreciate in value unless it is properly utilized. Heterogeneous markets catalyze fast changes in customer needs. At the same time, previous data about certain customer behavior might become inaccurate in an accelerated pace. The only way for the company to benefit from understanding the customer’s needs is shorten the cycle between need recognition and response.

Based on this argumentation, assets lose their value over time, thus companies should manage customer knowledge by integrating new data while eliminating old one. As customer needs and knowledge are exposed to fast changes, the generated knowledge stock has a higher decaying rate. To overcome this, companies must insure the input of new data to prevent or decrease the process of data - thus, customer knowledge - erosion. In this vein, the following assumption is deduced:

RP 3: The older the data becomes, the less value it possesses for generating analytical customer knowledge, and thus the more challenging it is to sustain a competitive advantage.

Interconnectedness of asset stocks - *accumulating asset stocks may depend on the level of other stocks.*

Besides the mediating role of predictive analytics in building knowledge-based asset stocks, predictive analytics is an asset per se, and its utilization plays an important role in building knowledge-based stocks. Both concepts are involved in a series of dependencies. Dierickx and Cool (1989) articulate it as the interconnectedness of asset stocks, which highlight the significance of dependencies of stock accumulation on other stocks. In this setting, building of analytic knowledge assets from data, by using predictive analytics, will be dependent on analytics competences (assets) a firm possesses. While data is a commodity itself and not a rare and unique resource (Rowley, 2006) and neither are analytics tools, the strategic integration of these two is a premise to the accumulation of valuable customer knowledge assets.

The full utilization of knowledge stocks requires a number of organizational and technological actions in order to establish the comprehensive system of knowledge discoveries. It is a very resource-intense process what reflects the amount of time needed for implementation. Thus, companies which benefit the most from the implementation of predictive analytics have already previous experience in analytics processes and techniques. Building upon this experience, they accumulated extensive knowledge on efficient ways of leveraging analytics. On the contrary, companies with no analytics experience, face significant challenges in the implementation of predictive analytics. Given this argumentation, the following research proposition will be deduced:

RP 4: The more experience in analytics company has, the greater the analytical customer knowledge stock it can accumulate, and thus, it possesses greater chances to sustain a competitive advantage.

Causal ambiguity - *the lack of visibility in asset stocks accumulation causalities and dependencies.*

However, even a similarity in asset stocks does not ensure the same outcomes for different ventures. Dierickx and Cool (1989) regard it as causal ambiguity. Causal ambiguity can be a source of sustaining competitive advantage and impedes limitations by competitors (Lippman and Rumelt, 1982). The process of managing customer knowledge generated from data, using PA, involves a range of factors which define ambiguity, related to this process. Given that knowledge, which resides at the customer side is rather tacit. This tacit feature, coupled with complexity of managing both knowledge and analytics stocks, power the level of causal ambiguity. In this vein, the following research proposition is developed:

RP 5: The more complex the processes of data processing and analytics utilizations for the purpose of generating customer knowledge assets are, the greater is the causal ambiguity, and thus the higher are the chances to sustain a competitive advantage.

3. Research Design

The study aims to spot the changes in customer knowledge management by identifying a new type of knowledge asset, namely analytical customer knowledge. Scrutiny indicated an extensive debate on knowledge as a resource, however, without a distinction between different types of knowledge. In this vein, to observe this issue in a resource-based perspective, we draw on the literature of (knowledge) asset stock accumulation by Dierickx and Cool (1989). Since the RbV on knowledge management does not offer any distinction between the different types of knowledge, we take it as a fundamental assumption that its premises - in the light of resource imitation - should not differ, when it comes to analytical knowledge assets. In this vein, we formulated a set of research propositions which reflect upon every characteristic of the asset imitability processes by Dierickx and Cool (1989).

Having deductively developed research proposition and yet, given the complexity and novelty of the topic, we approach these in a scope of qualitative research. To contrast the reality against the theoretical conceptual foundations, we apply an interpretative case study strategy for deductive reasoning (Merriam, 1988). A case study enables observation of concept within its real-time context (Yin, 2009).

Table 1. Case studies overview

Case study	Company	Industry	Data
Case 1	Company A	Analytics vendor	-interview -memos -secondary user cases
Case 2	Company B	Analytics vendor	-interview -memos -secondary user cases
Case 3	Company C	Expert (consulting)	-interview -memos -secondary user cases
Case 4	Company D	Energy sector	-interview -memos -company website
Case 5	Company E	Public sector	-interview -memos
Case 6	Company F	Finance (investments)	-interview -memos -company website
Case 7	Company G	Healthcare	-interview -memos -company website
Case 8	Company H	e-commerce	-interview -memos

In this vein, eight case studies, based on primary and secondary data, were developed. Case studies are able to provide a comprehensive understanding of the analytical knowledge context, as well as its positioning within the field of knowledge management. The peculiarity, fueling complexity, is determined by the number of sides (perspectives) being involved in the process of generating analytical knowledge. Knowledge generation and management takes place at the manufacturing/service company side, yet coupled with the managing of analytics, with its know-how residing at the analytics vendor side. To avoid the biases of a one-sided understanding of the nature of analytical customer knowledge generation, the perspectives of user companies, vendors, as well as field experts are involved.

Primary data was collected from semi-structured interviews, transcribed and anonymized. Enriched by the data from firm websites, user cases, webinars on the respective topic offered by the companies, and firm reports, eight cases were completed. The overview of the case study fundamentals is provided at the Table 1.

4. Analysis

4.1. Unfolding New Horizons of Customer Knowledge Management

Technological development has a tendency to change the nature of customer knowledge in two aspects: it changes the relationships between the processes of managing data, information and knowledge about and from customers under the knowledge management umbrella (Rowley, 2006); and it introduces a new type of knowledge, so-called analytical knowledge. The clear distinction between the different types of knowledge based on the sources, offered by the literature on customer knowledge management, drifts towards becoming obsolete. Companies with prevailing online presence and activities generate Big Data which embraces and articulates the whole variety of knowledge, grounded in customer behavior. A glimpse in the real business world provides great varieties of companies, especially service companies, which successfully leverage these data using analytics (Hair, 2007).

The majority of studies on customer knowledge claim that the knowledge from customers, generated through personal interaction between a customer and an employee, provides the most useful value for the companies (Gebert *et al.* 2003). Evaluating the value and retrieving the knowledge is very limited by the possibility of physical interactions within such an approach. In the era of digitalization of service provisions and firms operating exceptionally online, triggers a reshaping of how the knowledge management sees customer knowledge at all.

The companies operating online generate Big Data; and any technological flavoring which comes together with it, including concepts of Business Intelligence and analytics, push this topic to IT departments. Knowledge management tends to exclude the concepts related to data and sees it as a list of facts which do not offer any specific knowledge-like value. Partly it holds true or rather it did. The earlier techniques and tools of data processing, like descriptive analytics, offered a limited value of data. They were processing it and presenting in joint and organized but half-static data. Eventually, it could answer the questions related to the past events, e.g. *'what happened?'* (Siegel, 2013).

The evolution of analytics heads towards an increasing value of data to discover the knowledge behind. In this vein, the view of data as a list of unconnected facts shifts towards seeing it as an articulation of knowledge from customers. The exploratory steps in this direction were already made by Tuomi (1999). The process of extracting knowledge from data, by recognizing specific patterns within data, was enabled by the techniques of data mining and machine learning, encompassed in predictive analytics. The insights generated by predictive analytics embrace data-driven approach for understanding customer behavior. The limitations of the customers' ability to articulate their needs were stressed by von Hippel (2005) already a long time ago. And in this regard hardly anything changed nowadays. Indeed, customers became more informed and knowledgeable; they share and exchange their opinion with other customers over online platforms. However, to gain knowledge which precisely unveils the customer needs remains very difficult, as it is tacit.

The value of customer behavioral knowledge is determined by the fact that customer behavior is driven by a variety of knowledge they possess the ability to retrieve and use this knowledge for a better understanding of customer needs and better customer integration - is a new task for the customer knowledge management. Such a customer knowledge, generated a processed through advanced analytics tools, represents a new niche of analytical customer knowledge in the knowledge management scheme.

These processes require extensive revision of the sources of customer knowledge and their perceived value. Integration of analytical customer knowledge requires an approximation of knowledge management with data management. The role of data in this regard plays a very important role in order to ensure the accuracy and quality of generated knowledge. Data management, in its turn, strives to ensure the high quality of data input but providing a data governance, as explained by Company B:

When it comes to data protection, confidentiality comes to play. Because you give the data to data scientists but sometimes they need a broader dataset. They would like to have an access to entire company data, having like a 'data lake' where you throw everything in but it is not that easy because of all the governance rules and security policies.

There are many industries and sectors which could benefit from tacit customer knowledge, but yet struggle to retrieve it. Their knowledge management processes are very limited by the physical interaction with customers due to industry or business model peculiarities. For example, Company G, operating in the healthcare industry, strives to assist problems of non-adherence with medication my looking at the patterns of patient behavior, like eating peculiarities (time and speed) and other activities or read from the gestures due to wearable. Further, machine learning and advanced analytics are able to recognize behavioral patterns and generated specific knowledge about each patient which medical companies can use to provide specific medical assistance. Such knowledge is extremely valuable for such companies, as according to Company G:

They have problems of customer involvement and customization of services.

Thus, customer knowledge management which embraces the processes of generation and integration of the knowledge *from* and *about* customers should embrace the new emerging type of analytical knowledge. This is particularly important for the companies that cannot interact with customer and accumulate customer knowledge, as an input for optimizing their value proposition.

4.2. Peculiarities of Analytical Customer Knowledge Assets

In the scope of sustaining a competitive advantage, the time dimension plays a crucial role through preventing asset imitability (Dierickx and Cool, 1989). In this vein, assets stocks can be accumulated over a longer period of time. In terms of analytical customer knowledge, the following two aspects should be considered: accumulation of knowledge per se, and accumulation of customer behavioral data which is a foundation of customer knowledge. As for the former, more knowledge and understanding of customers facilitate the matching of customer needs, better value propositions and thus, sustaining a competitive advantage over potential competitors. However, dynamic environments undermine the value of stocks as such. Current volatile business markets set the need for firm agility rather than static asset or resource possession. The ability to generate specific customer knowledge, as an input in decision-making processes, upgrades the response to customer needs, optimizes firm resources and processes, and thus, ensures its competitive market position.

I am completely convinced that the company that does predictive [analytics] in the long-run, over 1000 decisions or 1000 processes, where predictive adds this incremental insight and in the long-run the decision of this company will be better. And then it will be a competitive advantage, compared to the customer who only relied on gut feeling (Company B).

As for the later one, accumulated data is important for generating analytical knowledge. The accuracy of insights, generated by predictive analytics, is proportionally dependent on the volume as well as quality of the data. It means that the minimum requirement for a sustainable analytics implementation is certain volume of historical data.

That [value of analytics insights] depends on the data they have. The call for predictive analytics always needs historical data (Company A).

Such data, applied to the customer perspective, embraces all the behavioral customer data, its search history, purchases, online behavior insights to mention a few. On the one hand side, the data volume depends on the time period it was generated, implying that the longer a company operates at the market, the more data it could have generated - which holds true for the research proposition 1.

On the other side, data volume depends on the activity and peculiarity of a firm business model and industry it operates in. Thus, data-driven startups, especially from the IT sphere or closely related to information and communication technologies (ICT) are likely to generate more reliable data over a short period of time, than a mature company over a longer period of time.

I think it has advantages to be an older company because you have more own data, you have more experience. The negative of being an older organization, is that often time complexity in some point will become a problem. What I mean is that the data acquisition becomes more and more difficult when you are in large and old company. Your processes are long and complex (Company B).

This example, however, undermines the validity of the RP1 in its pure fashion. In this vein, rather business peculiarity and its organizational culture define the nature of the data input, and thus, the value of analytical customer knowledge, as well as its positioning within the customer knowledge management. Applying this conclusion to a conceptual end, it questions the view on the time dimension in the scope of the RbV, and specifically on the asset stock accumulation. In terms of analytical knowledge as a resource, an ability to utilize asset flows to generate time-specific customer knowledge is more important than generating an asset stock per se. It challenges the static view on the asset stocks value and elevates the role of dynamic managing of knowledge assets, partly shifting the emphasis towards asset flows.

Thus, time compression diseconomies, as defined by Dierickx and Cool (1989), do not fully apply to analytical knowledge, in the scope of considering it as a source for sustaining a competitive advantage. In the contemporary business settings, a competitive advantage is defined by the company agility - an ability to respond to changing (customer) needs in a prompt way. Thus, not a stock of customer knowledge, but an ability to extract specific and relevant knowledge inputs ensures a firm’s competitive advantage.

Another data characteristic, which determines the quality of analytic knowledge and appeared vivid in empirical findings, is data quality and variety. The less noisy and more vectored data facilitates drawing a more comprehensive picture of customer needs, thus, generating more accurate analytical knowledge about customers.

The clear and clean data governance and structure is fundament on which everything sits. If you have flown data, if you don't have cleaned data structure, then what you see in analytics will not be the truth (Company B).

We are able to generate data which shows customer behavior from different perspectives. And that is great! We some more full pictures of customer needs and know exactly how to approach customers on an individual level (Company H).

In this regard, mass efficiency principle is not the only that sustains a firm competitive advantage, although the volume of historical data is significant - as analytics input - as well. In a pure fashion, the mass efficiency principle does not apply to analytical knowledge stocks. The greater focus in this regard deviates from the value of mass asset stocks to managing the flows. Indeed, rich, various, clean datasets are prerequisites of building appropriate knowledge stocks. Thus, RP2 which predominantly addresses the issues of quantity, in case of analytical knowledge stocks, should consider the quality dimension on an equal level. Great volume of data does not ensure prevent its imitability, as data should be properly processed to unfold its value.

Data will be commodity in next few years. Data, in a few years, will never be a competitive advantage (Company E).

Customer needs are changing very rapidly what determines the depreciation of respective analytical knowledge stocks. What was holding true for a certain customer yesterday and was articulated (mirrored, represented) in predictive analytics insights, today most probably will not be accurate anymore. However, despite the close correlation and dependency between data and respective analytical knowledge assets, knowledge has a way greater degree of depreciation than the data. Data, which constitutes historical data, despite its gradual outdating, still preserves its value and role in training predictive analytics models (Nisbet *et al.* 2009).

Data becomes less relevant overtime but it still produces something. After some time I cannot say that it [data] becomes old and useless [...] but it will not be clean data because it is going to improve and become better (Company G).

Although historical data and its volume plays significant role in building valuable analytical knowledge, it also has a tendency to outdate. However, it is rather a natural process in the context of predictive analytics. As far as data flows are managed to constantly fuel analytics models, the accuracy of insights and value of the customer analytical knowledge will not be jeopardized by an ‘aging’ processes.

Another example, when data outdates instantaneously, is a rapid business model innovation, when the company completely changes the focus and questions which were addressed by analytical models. Thus, current data flows might not meet the requirements of new business needs, thus they need to be completely rearranged.

Addressing RP 3 in general, the issue of asset erosion relates rather to depreciation of asset flows than asset stocks.

The research on analysis of analytical customer knowledge indicated the dependencies and interconnectedness between the knowledge per se, underlying data and predictive analytics. Accumulation of this particular type of customer knowledge is entirely connected to the level of technology and analytics development at the company. And prior experience in analytics appears to be a driver in fostering analytical knowledge accumulation.

[Leveraging analytics] there has to be buy-in from senior management. But they are people who were working for years in energy business and nobody heard of analytics (Company D).

However, not only prior experience but organizational readiness and openness towards new ways of facilitating customer involvement play important role in knowledge accumulation.

Our senior management was there for 20 years and their decisions were based on gut feelings and they didn’t use data to support any of their decisions. But then old management was replaced with new management who said “We need it [analytics]” (Company F).

It [analytics adoption] is rather depending on the business culture of the company: how open are they on new things, how open are they to try new things, how open they are into going to calculative risks (Company A).

These findings extend the interconnectedness between accumulation of knowledge and predictive analytics (as discussed in RP 4) to a more complex dependencies between data- and analytics-related competences.

Although the utilization of analytics tools and generating of certain insights might seem absolutely specific, expected, reliably and straight-forward, at the end of the day the decision is made as a combination of analytic insights and managers ideas. The fact of the involvement of a human factor in this process is already a source of causal ambiguity. Separation and distinction of the level of contribution of those two to the final result is impossible. Thus, even if competitors use the same technology and, for example, buys-in same data, the final outcome most probably will differ. Even the experts in analytics field, who assure the technology value and accuracy of analytic insights, stress the importance using own managerial experience and knowledge in the final process of decision making.

It [insights generated using PA] adds an additional valuable dataset and data point which helps you make the right decision but should not be considered as kind of the only source of truth. If the predictive model says "go" and you go - I would not ultimate it for bigger decisions in that way (Company B).

Causal ambiguity has high chances to occur within the processes of generating customer knowledge, using PA. This is caused predominantly by the complexity of processes and integration of various technological and human factors into the decision-making processes. Such a constellation impedes imitability of knowledge stocks and facilitates sustaining competitive advantage - what comes in line with RP 5.

5. Conclusions

This study intends to shed light on understanding the peculiarity of customer knowledge, generated through predictive analytics, and its positioning within customer knowledge management. The novelty of the study lies in the business perspective on the topic, dominated in IT literature. The topic of data utilization for knowledge generating is transmitted and applied against the concept of asset stocks accumulation. Thus, the study extends the debate on managing customer knowledge in the scope of technological advances, by merging this concept with elaborations from the data science.

This study explores the ways to facilitate customer integration in a new level, especially for the companies that do not have possibilities of physical interaction with customer. In this vein, data mining technologies, specifically predictive analytics, broaden horizons of data management. Very useful and unique information which eventually constitute market needs resides at customer side. For online operating companies this might be the only customer input they can utilize. However, data – as an articulation of customer behavior – has a value only if it is properly managed and specific knowledge has been discovered within sets of data (Fayyad *et al.* 1996).

The value of customer knowledge is particularly crucial for service companies, which are more exposed to customer integration for optimizing their value proposition and remaining customer-oriented. The importance of the customer is a fundamental premise of value-co creation (Vargo and Lusch, 2004). However, the concept of customer knowledge integration is mostly generalized and regarded as an 'input from customers', while its nature is ignored and considered as not important. In this vein, the studies on customer involvement - at most - emphasize the importance of network and interactive cooperation with the customers. It can be deduced that the authors talk about some 'conscious' customer involvement - when customers to some extend are aware that their opinion is being heard and considered.

This study, however, unveils the existence of a different type of customer knowledge, rather 'unconscious' by nature. In many cases, closely related to internet activity, like e-commerce or banking, technology enables the generation of a significant amount of information (Big Data) about customer behavior. It lifts the discussion on customer knowledge management to a different level, where the company has precise visibility of customer needs. Another peculiarity is that the 'a customer' is regarded not at the group level but individual level, what enables precise responses to specific individual customer needs and developments of customized offerings.

The majority of the studies regard customer involvement on the conscious manner, implying purposeful personal interactions (e.g. as a response to certain customer claims, feedback etc). Even though such activities provide an input for service innovation, their limited and occasional occurrence restrains the consistence of knowledge generation. Regarding the proactive or reactive nature of customer knowledge accumulation, the knowledge integration is always predominantly explicit and conscious. The new trends, continuously evoking within the business realm, facilitate the uncovering of hidden potential of the implicit knowledge embedded into customer behavior. This is particularly vivid among service companies, exposed to extensive online interactions. RbV stands on the need to generate resources over time, its mass efficiencies in order to sustain competitive advantages. However, this research indicated that (customer) knowledge generated using analytics is characterized by the need to manage its flows rather than accumulating stocks.

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