Towards Value Proposition Mining – Exploration of Design Principles

Short Paper

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Abstract

Organizations must be increasingly able to adapt to ever-changing environmental conditions. For the resulting transformations, companies need a solid knowledge of their current business models to transform them towards prospective target models. However, established business model creation frameworks are manual, error-prone, time-consuming and highly subjective. Following a design science research approach, this work proposes the development of an artefact for business model mining to overcome the weaknesses of manual approaches. In a set of meta-requirements, design principles and a prototype, it will be shown how qualitative value propositions can be extracted from companies' web pages. Embedded in a comprehensive data-driven artefact, it should be possible to extract the whole business model of a company through organizational information and its systems. This provides a broader view on a company's value creation next to existing top-down approaches and enlarges existing business model research.

Keywords: Value Proposition, Business Models, Design Science Research

Introduction

Digital transformation forces companies to transform their business models (BM) to adapt to their dynamic environment (Teece 2010). Beside technical innovations and globalization, the pervasive pressure for cost reducing as well as shorter time-to-markets drastically change the boundary conditions for organizations. All of these unexpected changes demand companies to adjust their BMs quickly (Magretta 2002; Chesbrough 2007). As a result, the traditional logic of doing business needs to be radically rethought and BMs should be redesigned (Piccinini et al. 2015). Otherwise, companies and their BMs face the risk of being displaced like video stores, who have been supplanted by online providers such as Netflix or Amazon Prime.

However, Johnson et al. (2008) as well as Demil and Lecocq (2010) describe that correctly defining the status quo business model of a company needs an exhaustive description of the current value creation mechanisms. Next to traditional approaches such as the Business Model Canvas (BMC) of Osterwalder (2004), data-driven approaches emerge as valuable alternatives (Augenstein et al. 2018). With data from enterprise systems such as enterprise resource planning (ERP), a current status of the value creation process of a company can be rebuilt objectively. Such systems capture structured data about the core BMC categories customers, resources, suppliers, costs, revenues, or sales channels as well as key activities. However, a key challenge is to (semi-) automatically extract the value proposition (VP) of a company, as this information is usually not kept in ERP systems. This is because a simple information retrieval of a web page can lead to wrong, too less/much information or one decides for uninteresting data related to the case one has to solve. Data Mining and a related describing algorithm can lead to an objective degree of abstraction of the relating value proposition. We will retrieve such an algorithm through scanning hundreds of web pages and find common elements, which can lead to such a describing algorithm for retrieving a more objective VP. Osterwalder and Pigneur (2010) define this VP as *"[...] the reason why customers turn to one company over another. It solves a customer problem or satisfies a customer need" (Osterwalder and Pigneur 2010, p. 22)*. This information can only be identified in organizational IS if one focuses on the offered products, services or bundles. However, there are many existing sources a company publicly provides to inform their customers about expected benefits of a product or service. Moreover, such data covers rather latent information on the customer value. On the other hand, companies and especially startups need to communicate their offering to customers and other stakeholders. Therefore, they rely on mainly unstructured textual data such as business plans, pitches, or online descriptions. To find a describing algorithm to mine the VP, we "mine" and classify information from unstructured textual data to achieve a close description of a company's VP and to realize a complete data-driven status quo of a firm´s offerings. Therefore, this research aims to answer the following question:

Which design principles need to be followed for a value proposition mining system, using unstructured textual data?

To answer this research question, we follow the Design Science Research (DSR) approach of Vaishnavi and Kuechler (2015). In previous work, we built a BM Miner which extracts a companies' BM from ERP data (Augenstein and Fleig 2017). However, mining qualitative elements of the value proposition like customers' benefits from ERP data is difficult. As a consequence, we want to enhance the BM Miner through an intelligent information extraction system which collects qualitative VP data automatically from web pages and classifies it accordingly. "Intelligent" means hereby that the system follows patterns and learns to extract data from web pages with new patterns. From a scientific point of view, we enlarge the basis of design knowledge for data-driven BM approaches. Furthermore, building such tools enables practitioners to make subject decisions of latent VP data more fact-based and objectively, which might create interest in domains such as venture capital investing or M&As.

The structure of the paper is as follows. In chapter 2, we present the related work and foundations for our project. The DSR project methodology is described in a more detailed way in chapter 3. There, we will describe our existing BM Mining tool and have a detailed look on the extension for VP Mining, which is the focus of this work. We also give a detailed overview of the data we use for this project in chapter 4. Following up, we give an overview of the requirements and design principles (chapter 5) which lead to a possible instantiation in chapter 6. Finally, we provide a summary, limitations and an outlook in chapter 7.

Related Work

In this section, we present the foundations of our work. We give an overview of BM frameworks and in particular of the value proposition of the BMC. The "Business Model" construct has been researched in literature for many years (Gordijn et al. 2000; Petrovic et al. 2001; Veit et al. 2014). An early definition of Timmers (1998, p. 4) is:

BMs are "an architecture for the product, service and information flows, including a description of the various business actors and their roles; and a description of the potential benefits for the various actors; and description of the sources of revenue".

This definition contains two different views on BMs. On the one hand, BMs can be seen as flow-based approaches that present the flow of the business value (Akkermans and Gordijn 2003). On the other hand, BMs can be seen as component-based and as a textual representation of the individual BM components (Burkhart et al. 2011). This approach is used more often, as for instance in the BMC (Osterwalder and Pigneur 2010). The BMC is highly accepted in academia and managerial practice and focuses on two main purposes: First, the purpose of the BMC is to provide a kind of moderation method to visualize the current way of value creation. Second, the BMC visualizes the current value creation of a company in a template, which is easy to use and standardized. Osterwalder and Pigneur (2010) divided this BMC into the following nine categories: Key partners, activities, resources, value propositions, customer relationships, channels, customer segments as well as cost structure and revenue streams. As a support for practitioners, they offer a set of guidelines to fill out the BMC correctly. These guidelines contain leading questions for each field of the BMC to make it easier for users to fill them out. Next to this traditional top-down approach, data-driven bottom-up approaches also exist (Augenstein et al. 2018). These approaches use data to retrieve a more objective view of the current value creation than the traditional BMC approach. Thereby, methods from process mining are also used. However, using ERP data to retrieve a BM is not possible for all categories. Especially the VP category is not easy to be retrieved from traditional ERP data.

Focusing on the category "Value Proposition", Osterwalder and Pigneur (2010) describe this building block as "the bundle of products and services that create value for a specific Customer Segment". The key focus of this category is how a company solves customer's problems, satisfies customer needs and shows what product and services are offered. In other words: The VP of a company reflects the creation of users' benefit through the whole value creation process (Wirtz 2011). The VP contains, thereby, benefit and value aspects of a business proposition. Through performance reviews, companies can check the extent to which value propositions are communicated to customers through the corresponding action programs and the profit from potentials associated with them (Wirtz 2011). In this context, the VP can therefore also be used for the development of new services offered by the divisions (Anderson et al. 2006). They classify the VP in "all benefits", "favorable points of difference" and "resonating focus" (Anderson et al. 2006, p. 2). As "all benefits", they see a simple list of all advantages for costumers. The class "favorable points of difference" considers the possibility for customers to choose between different alternatives. It considers the factors which present the company in a way that makes the customer choose the product or service of this specific company (Osterwalder and Pigneur 2010). The third class is the "resonating focus". For Anderson et al. (2006) it is the gold standard of the value proposition description. It reflects the custom-fit and individual solution for each customer. This means that supplier and customer both know the benefits of the specific product or service and it perfectly matches with the desires of the customer. To sum it up: "A Value Proposition creates value for a Customer Segment through a distinct mix of elements catering to that segment's needs." (Osterwalder and Pigneur 2010, p. 23). Thereby, these value propositions can be divided into qualitative and quantitative values (Osterwalder and Pigneur 2010). Examples for quantitative values are prices or speed of service. These values can be measured through the respective key performance indicators (KPI) and can therefore be extracted from ERP data. For example, Frow and Payne (2011) have a look on value propositions from a more quantitative view of stakeholders. Qualitative values like design or customer experience are much harder to extract and measure from companies' ERP data. For example Lindič and da Silva (2011) focus also on qualitative VP elements in their work and proposed a framework for identifying value proposition elements. We will stop here and develop a tool extracting qualitative values from information sources like a company's web page. How we want to do this is shown in the following chapter.

The Design Science Research Project

In order to enlarge BM mining through a VP mining system, which derives qualitative elements (e.g. users' benefits, problem solving etc.) for the VP category of the BMC, we apply a Design Science Research (DSR) project following Vaishnavi and Kuechler (2004, 2015). We use this concept because of its loop approach, which we find adequate to retrieve a solution that is closely related to the problem and to be able to learn rapidly from each cycle. In this context, we perform three design cycles in total (Figure 1). We already performed and published Design Cycle One (Augenstein and Fleig 2017; Augenstein and Maedche 2017). In it, we develop a BM Mining tool, using ERP data and Process Mining methods to retrieve a BM from ERP data. For the key activities, we additionally use a process mining algorithm to identify main activities. We then structure and aggregate this information to provide a good overview of the current value creation for the user. The user then gets a data-driven BMC they can adjust to their own views and knowledge. However, one weakness is that quantitative but not qualitative VP elements can be mined from ERP data. As a result, this work will focus on qualitative "Value Proposition Mining" in the Second Design Cycle. In this second cycle, we will retrieve requirements and design principles from literature and from our practical insights to develop a BM Mining feature which can automatically retrieve information of company web pages. We will then combine and evaluate the BM Miner with the Value Proposition Mining feature together.

General Cycle	First Design Cycle	Second Design Cycle
Problem Awareness	• Literature Review • Interviews with Industry Partners • Workshop with students	• Value Proposition is represented quantitative, but not qualitative through the „BM Miner“
Suggestion	• Data-driven Business Model Mining Tool for automated BMC generation. • Requirements and Design Principles	• Qualitative mining of the value proposition through the use of information from websites
Development	• „Business Model Miner“ prototype under consideration of Requirements and Design Principles	• Extension of the tool through a web crawler and an ontology for possible qualitative value propositions
Evaluation	• Field study: Defining top-down a "gold standard" in a workshop with industry partner executives and compare it with results of the "BM Miner"	• Case study: Scanning 200 webpages with the web crawler and comparing the results with the "gold standard" of Cycle one.
Conclusion		• Design Knowledge • Extended BM Tool

Figure 1. Design Science Research Cycles (according to Vaishnavi and Kuechler (2015))

We already performed **Design Cycle One**, as mentioned before. In this cycle, we conduct a literature review to retrieve the theoretical needs of science towards a BM mining. We combine those findings with interviews from our industry partners to also find out the business needs. Finally, we perform workshops with students to find out general challenges of business modelling. Out of these theoretical, practical and general needs, we formulate requirements and design principles for a BM Mining tool. As the BMC approach is a top-down approach, one weakness is the high subjectivity of the elements. People fill out the BMC at the best of their knowledge. However, combining this top-down approach with a bottom-up BM mining can make the resulting BMC more objective through the data support. These needs, requirements and design principles are then considered in the development phase of the tool. We build a BM Mining prototype and evaluate it in a field study. Together with the BM experts for each BMC category, we create a "gold standard" through interviewing the respective persons and finding out the main elements for each category of the BMC. We perform several rounds of workshops to get a rigorous view of the company's BM. We then compare the result of the BM Mining tool with this gold standard and measure the differences. We will do the same with the top-down approaches, which the BM experts of the company modeled. We then show that the differences of the BM Mining tool are smaller than with the traditional top-down approach. We find out, that the VP category differs strongly from the gold standard, as we can only mine quantitative attributes.

To solve this challenge of missing qualitative attributes in the value proposition mining, we updated the problem awareness in **Design Cycle Two**. Additionally, we do a literature review on VPs to get an overview about existing papers related to BMs. While objective VPs can be found easily in business reports or ERP data, the true benefit lays in the subjective principles, which are not easy to retrieve. This is because for example Coca Cola offers quenching the thirst and a great lifestyle feeling as VPs which cannot be reflected in objective VPs but in subjective ones, which are the success factors for the company selling their product. In this cycle, which is in the focus of this paper, we suggest mining the VP category through the use of webpage information a company provides for example on its homepage. Therefore, we first create a taxonomy of possible value proposition elements through scanning 200 webpages by hand. We then use a web crawler to extract the value proposition of a company and hand-label the data for each category of the taxonomy. Based on this, we will train a classifier to automatically identify and categorize the unstructured textual data according to the taxonomy. Therefore, the classifier will learn through experience from additional data and improve in classifying suitable value propositions automatically. This will be evaluated as follows: After training the classifier with the data of the 200 webpages, we use the webpage of each of our industry partners. We then measure the accuracy, precision, recall and F1 Sore of this mined value proposition and the mentioned gold standard that we already used in cycle one. These measures, as for example the recall, are common measures to determine the quality of the elicitation results (Cleland-Huang et al. 2007; Casamayor et al. 2010; Gacitua et al. 2011). After this, we compare this with the results of the BM Miner and the top-down approach of cycle one and expect a more precise value proposition with this approach. Moreover, we will collect additional web data to test the performance of the classifier in terms of generalization. The result will be the tool in design cycle three, which not only uses the BM Miner but also the VP miner and the findings of this cycle. The result will be that a company can (semi-) automatically retrieve its current BM. This should help for example to transform the BM more adequately to the given starting position (Augenstein et al. 2018).

Finally, we develop an integrated BM Mining tool which can mine the whole BMC of a company. Therefore, we combined the BM mining tool of cycle one and the VP miner of cycle two and developed the integrated BM Mining tool. The result of the whole DSR project will be twofold. First, we improve the design knowledge for data-driven business modelling as a theoretical contribution through detailed requirements and design principles with focus on BM and VP mining. Second, we will publish an extended BM tool to support practitioners in a more objective business modelling. The data we use is presented in the next chapter.

Data

For the second cycle of our DSR project, we use the information of 492 homepages of different companies in the Internet of Things category on the startup database CrunchBase (www.crunchbase.com) to create a VP taxonomy and train the classifier. We see the number of 492 companies as adequate because we can consider different facets and various ways of presenting the VP on homepages. We want to mention that we do not use this data for evaluating/validating our approach. We focused on companies with only one product or service because some companies have more than one BM, which makes it hard to collate the elements to the respective model. The addressed industries contain several categories to include a broad range of VPs. For the taxonomy, we created a semantics related to the value proposition of a company. Thereby, we focused for example on the customer wants and needs (i.e. problem), the customers value, the problem solving, the product or service and many more. For each category, we searched the related terms on the webpage manually and created a common taxonomy the classifier can use. For the BM Mining tool of cycle one, we used ERP data from our industry partners for all categories except the “Key Activities”. For this category, we used process mining algorithms to find the relevant information for the BM. We thereby focused on various processes of the company. Generally, we followed the generic structure of Osterwalder and Pigneur (2010). Consequently, we ensure that the mined BMC is similar to the traditional BMC approach to support a better comparability between the different approaches and the gold standard in the evaluation. The advantage of this approach is the possibility of data triangulation with the different forms of qualitative and quantitative data and the different data acquisition techniques including transactional data from ERP systems and interviews with different groups of people in the companies (e.g. Remus and Wiener 2010). One has to add that this transactional data is not the same data, used in the BM Miner but additional data specialized on the VP of a company.

Conceptualization

In this section, we propose our meta-requirements and tentative version of design principles for our value proposition miner. As mentioned before, we want to create an intelligent information extraction system which collects value proposition data automatically from websites. We decided for websites because we see herein the biggest chance to collect “subjective” VPs. As mentioned, other sources like business reports or ERP data contain VPs too, but these are more abstract and rarely represent the reasons why people decide for the product or the service. However, this is reflected in the webpages, which need to address the users with their needs appropriately. “Intelligent information extraction system” means hereby that the system follows patterns and learns to extract data from websites with new patterns. Analyzing 200 webpages of the companies, we discovered that the presentation and proposition of the value differs enormously among each other. While some companies for example use the starting page to present the value with concrete bullet points, some others hide the information in a text on separate pages. In general, the representation of the value proposition varies not only between qualitative, quantitative or both elements but also between the representation of the value proposition. This makes it difficult to collect the relevant data tool-supported without a clear structure of this information. However, the automated collection of the data in an efficient way is important because the user is not prepared to accept long performance times for the data extraction and also the correctness of the results plays an important role. In general, a web crawler cannot be configured individually for all web pages, but it should be usable for each single web page without any further effort. As a result, we demand the first meta-requirement (***MR1***) that for a data-driven value proposition appropriate data needs to be found and collected tool-supported e.g. through a web-crawler.

MR1: To enable data-driven creation of the value proposition, appropriate data needs to be identified and collected tool-supported.

As mentioned above, each company presents their value proposition on a homepage differently. To be able to compare different value propositions and to refer the descriptors to a document for indexing the facts contained therein, a structure of the data is necessary. A controlled indexing for example in an ontology can build a data set which can show individually the value proposition of a company. At the same time, the whole amount of data can build a base to train web crawler for finding the relevant information on very specific or unstructured web pages. Beside this, it is important to structure extracted data for users to increase their comprehension about the content of the data (Augenstein et al. 2018). So, we propose that extracted data should be structured intelligently and uniformly in the second meta-requirement (***MR2***).

MR2: To guarantee comparability of different value propositions, the extracted data should be structured in a unified way.

Next to the structure of the data, the amount and level also plays a huge role for the understanding of the user. The amount of data should be reduced to reflect the logic how a company creates value on a suitable level (Osterwalder and Pigneur 2010). Therefore, the relevant data needs to be aggregated (Augenstein and Fleig 2017), as we demand in meta-requirement three (***MR3***). It is also important to aggregate the information to not get an incomprehensible ontology. A comprehensive ontology can also build the base for ontology learning.

MR3: To chronicle only relevant elements of the value proposition, the collected data should be aggregated.

To build an intelligent information extraction system which collects value proposition data automatically from websites, the meta-requirements must be translated into concrete design principles. As one goal is to collect the data tool-supported, appropriate schemata to derive the value proposition from data need to be defined. Using an ontology to describe the value proposition and the necessary data helps to focus on the relevant information on a website (**DP1**). A web crawler can then retrieve this data automatically from the website (**DP2**). However, the web crawler might find a lot of relevant information depending on the web page. As demanded in MR2 and MR3, this raw data should not be presented to the user directly but should be appropriately prepared and be usable. To enable a comparability of the data and to present only relevant data to the user, it needs to be structured. Therefore, a machine learning classifier will be enabled to classify the raw data into the appropriate knowledge representation schema (**DP3**). On the one side, value propositions of different companies or BMs can be compared with each other. On the other side, the user can access the complex information more easily. As mentioned, the value proposition miner should get a kind of intelligence to be able to find all value proposition information on web pages. This is because not all companies describe their value proposition on the start page, but the information is distributed to one or more special pages. A non-intelligent web crawler might miss some of this information. With artificial intelligence, the web crawler should learn while extracting web pages and should therefore be able to cover a wide spectrum of different kind of value propositions on web pages. An ontology learning method (**DP4**) will thereby help him to find the relevant new categories. Therefore, an intelligent algorithmic word embedding approach (e.g. word2vec) should enable the value proposition miner to identify and learn novel sub-categories of the ontology independently. Such approaches use two-layer neuronal networks to reconstruct the linguistic context (i.e. meaning) of words (Mikolov et al. 2013). As a result, the more web pages are scanned, the more accurately it can identify the relevant information.

Design Principle	Related MR	Description
DP 1	**MR1**	**For an identification of appropropriate data, a value proposition ontology needs to be created.**
DP2	**MR1**	**An unstructured data crawler collects the appropriate data to create a data-driven value proposition.**
DP3	**MR2 & 3**	**For structuring the collected data, a machine learning classifier will be enabled.**
DP4	**MR3**	**Ontology learning methods will be approached to chronicle only relevant value proposition elements.**

Table 1. Description of the Design Principles (DP) and related Meta-Requirements (MR)

Instantiation

To instantiate our proposed design principles into an IT artefact, we first created an OWL ontology with the open source ontology editor Protégé (www.protege.stanford.edu). We then build a Python-based web crawler on the Scrapy framework (www.scrapy.org) with which we crawled the unstructured textual descriptions of the startups' value propositions. We then hand-labeled each of the startups' descriptions following the categories of our ontology that was initially developed. All data is stored in a relational SQL database. After this, we preprocessed the data through tokenization, normalization (stemming and lemmatization) and noise removal (e.g. markup data etc.). This data is then used to train a machine learning model. Therefore, we build a Naïve Bayes algorithm on the Python-based machine learning framework TensorFlow (www.tensorflow.org). Naïve Bayes constitutes a probabilistic classifier that is based on the "Bayes Theorem" (Murphy 2012). One of the main assumptions of Naïve Bayes is the conditional independence of the data features. This means that Naïve Bayes does not consider any correlations between a set of features that constitute a class variable. Features in our context (i.e. text classification) constitute single words. The presence of features is used to predict a certain class. To do so, words are represented in a 2-dimesional word document term matrix also known as Bag of Words (Thang et al. 2010). In the next steps, we will implement a Word2Vec algorithm to automatically identify new categories for the ontology as we proceed the mining process. Additionally, we created a web application as GUI to visualize the mined VPs to users. This can be seen in the following figures.

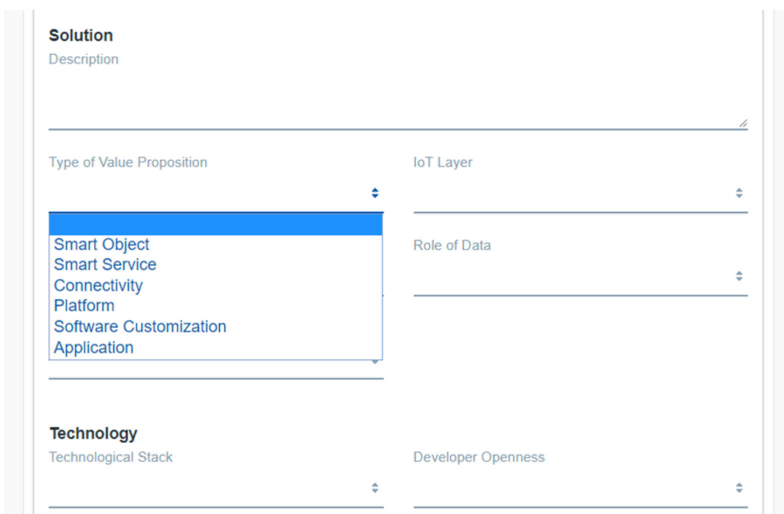

Figure 2. Exemplary Screenshot of the Ontology Visualization in the Web App

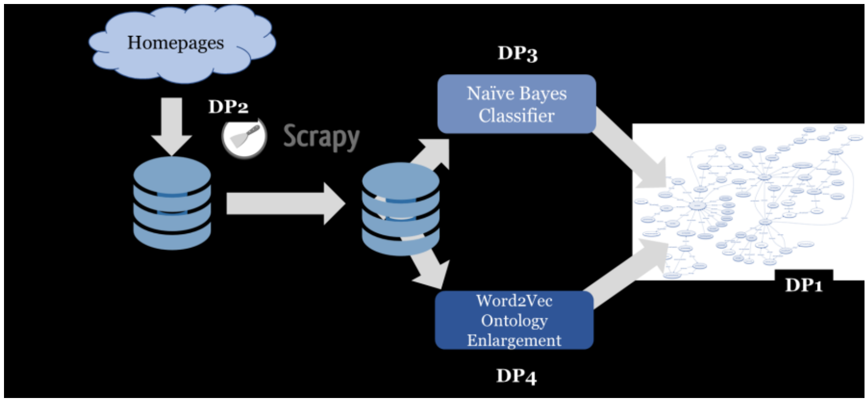

Figure 3. Architecture of the Value Proposition Mining Tool

Through this approach we want to extract the VP of a company automatically. However, we think that human input should not be excluded, as previous studies (e.g. Augenstein et al. (2016)) have shown. One reason is, that some people have special and important knowledge. Therefore, we decide for a semi-automated approach: First, the VP Miner proposes a set of VPs. Then the user can change elements and it is possible to add or to delete elements. The result is a set of VPs which is created bottom-up through mining different information sources like web pages and which is evaluated top-down through decision makers.

Conclusion

For decision makers, BMs are very important to make good decisions or during a transformation phase. With our research project, we want to provide an effective and efficient modelling method, which is advantageous compared to existing approaches in terms of effort, objectivity, flexibility, and costs. In this work, we present a novel and innovative approach to explore design principles to improve our and other existing approaches of BM mining with focus on qualitative VPs retrieval. Our artefact automatically discovers the VP of a company through the company's own web page. In our DSR project we use Osterwalder's (2004) BMC as a representation of BMs which is widely accepted by scientists and practitioners. We started to build an ontology and a web crawler which automatically extracts the value proposition of a company's homepage. Therefore, we scanned 200 web pages by hand and built an ontology. By relying on companies' data as a bottom-up approach, we target the satisfaction of an increased objectivity for the representation of the value creation. Furthermore, we want to increase the correctness of a company's BM and decrease the modelling effort for users.

However, in its current form our work has some limitations. First of all, if a company has more than one BM, the system cannot relate the VP elements to one specific BM. Second, in contrast to the more objective ERP data, information on web pages are also human-made and therefore not fully objective. However, we assume, that the data on homepages is checked by more than one person and therefore more accurate compared to the traditional BMC modeling process by only one person. Additionally, the web crawler only understands the English language so far. As many web pages also have an English version, we assume the lack as low. Future work can have a look at this challenge and extend the system through multiple languages. For our DSR project, we want to complete, evaluate and improve the current approach. Thereby, we will have a look at different methods for mining, too. Furthermore, it is conceivable that the complete BM Miner will function as a decision support system. Thus, the BM of a company can be observed steadily and changes in the value creation can be detected rapidly. Additionally, we want to get more insights into the influencing factors of the meta-requirements and the environment which lead to these meta-requirements. Some questions we want to answer are: How does a BM change over a period of time? How does an automated method save and show these changes to users?

To conclude, we think that our proposal for BM Mining including the mining of VPs significantly improves the capability of organizations to create knowledge about the organization and serves as a solid base for transformation decisions by providing a more objective view of the current value creation of a company.

References

Akkermans, J. M., Gordijn, Jaap 2003. "Value-based requirements engineering. Exploring innovative e-commerce ideas" in Requirements Engineering 8 (2), pp. 114–134.
Anderson, J. C., Narus, J. A., van Rossum, W. 2006. "Customer value propositions in business markets" In Harvard Business Review 84 (3), pp. 1–8.
Augenstein, Dominik; Citak, Murat; Ullrich, Meike; Vetter, Arthur (2016): Experience Report. Social BPM Lab enhanced with participation of professionals. In Modellierung 2016. Workshopband. Hrsg.: S. Betz.
Augenstein, Dominik; Fleig, Christian (2017): Exploring Design Principles for a Business Model Mining Tool. In ICIS 2017. Association for Information Systems. AIS Electronic Library (AISeL).
Augenstein, Dominik; Fleig, Christian; Mädche, Alexander (2018): Development of a data-driven business model transformation tool. Digital and Globalized World: 13th International Conference DESRIST 2018.
Augenstein, Dominik; Mädche, Alexander (2017): Exploring Design Principles for Business Model Transformation Tools. In ICIS 2017. Association for Information Systems. AIS Electronic Library (AISeL).
Burkhart, T., Krumeich, J., Werth, D., Loos, P. 2011. "Analyzing the Business Model Concept - A Comprehensive Classification of Literature" In ICIS 2011 Proceedings.
Chesbrough, H. 2007). "Business model innovation. It's not just about technology anymore" In Strategy & Leadership 35 (6), pp. 12–17.
Demil, B., Lecocq, X. 2010. "Business Model Evolution: In Search of Dynamic Consistency" In Business Models 43 (2–3), pp. 227–246.
Frow, P., Payne, A. 2011. "A stakeholder perspective of the value proposition concept" In European Journal of Marketing 45 (1/2), pp. 223–240.
Gordijn, J., Akkermans, H., van Vliet, H. 2000. "Business Modelling Is Not Process Modelling" In Conceptual Modeling for E-Business and the Web, 2000 Proceedings, pp. 40–51.
Johnson, M. W., Christensen, C.M., Kagermann, H. 2008. "Reinventing your business model" In Harvard business review 86 (12), pp. 57–68.
Lindič, J.; da Silva, C. M. 2011. "Value proposition as a catalyst for a customer focused innovation" In Management Decision 49 (10), pp. 1694–1708.
Magretta, J. 2002. "Why Business Models Matter" In Harvard Business School Pub.
Osterwalder, A. 2004. "The Business Model Ontology – A Proposition in a Design Science Approach"
Osterwalder, A., Pigneur, Y. 2010. "Business model generation. A handbook for visionaries, game changers, and challengers" Toronto.
Petrovic, O., Kittl, C., Teksten, R. D. 2001. "Developing Business Models for Ebusiness", ICEC 2001
Piccinini, E., Gregory, R. W., Kolbe, L. M. 2015. "Changes in the Producer-Consumer Relationship-Towards Digital Transformation"
Remus, U., Wiener, M. 2010. "A multi-method, holistic strategy for researching critical success factors in IT projects" In Information Systems Journal 20 (1), pp. 25–52.
Teece, D. J. 2010. "Business Models, Business Strategy and Innovation" In Long Range Planning 43 (2-3)
Vaishnavi, V., Kuechler, W. 2004. "Design Science Research in Information Systems"
Vaishnavi, Vijay; Kuechler, William (2015): Design science research methods and patterns. Innovating information and communication technology. Second edition. Boca Raton: CRC Press LLC.
Veit, D., Clemons, E., Benlian, A., Buxmann, P., Hess, T., Kundisch, D. et al. 2014. "Business Models - An Information Systems Research Agenda" In Business & Information Systems Engineering.
Wirtz, B. W. 2011. "Business model management. Design - instruments - success factors." 1. ed.: Gabler.