Association for Information Systems
AIS Electronic Library (AISeL)

Research Papers ECIS 2018 Proceedings

11-28-2018

Constituent Elements for Prescriptive Analytics Systems

Karolin Stefani
Technische Universität Dresden, karolin.stefani@tu-dresden.de

Patrick Zschech
Technische Universität Dresden, patrick.zschech@tu-dresden.de

CONSTITUENT ELEMENTS FOR PRESCRIPTIVE ANALYTICS SYSTEMS

Research paper

Stefani, Karolin, TU Dresden, Dresden, Germany, karolin.stefani@tu-dresden.de

Zschech, Patrick, TU Dresden, Dresden, Germany, patrick.zschech@tu-dresden.de

Abstract

Prescriptive analytics has emerged as a technological driver in data-intensive enterprise environments, as it tries to transform valuable insights into actionable recommendations and act upon them in order to meet business objectives. The basic idea is to go beyond the findings of descriptive data analysis and predictive modeling to answer the questions "What should be done?" and "Why should it be done?". However, there is often an inconsistent understanding about constituent elements of prescriptive analytics, which may hinder the development of adequate information systems. For this reason, the paper deals with a conceptualization by conducting a systematic literature review. The research goal is to extract fundamental aspects and facets from different perspectives and consolidate them into a coherent view towards a common understanding of a prescriptive analytics system.

Keywords: Prescriptive Analytics, Big Data Analytics, Decision Theory, Decision Science

1 Introduction

In recent years, utilizing big data has been established as a core topic in information systems (IS) research and practice (Abbasi et al., 2016; Chen et al., 2012; Müller et al., 2016). The term 'big data' refers to a situation where the process of digitization leads to an increasing availability of large collections of data that is generated with increasing frequency from multiple sources and heterogeneous systems (Chen et al., 2012; Constantiou and Kallinikos, 2015; De Mauro et al., 2015). Within an organizational context, this kind of ubiquitously generated data can be seen as a primary business asset to establish data-driven business processes and fact-based decision-making (Abbasi et al., 2016; Zschech et al., 2017; Mikalef et al., 2017). Beneficial promises of dedicated data utilization include better transparency, improved performance measurement or the support and replacement of human decision-making with automated algorithms (Manyika et al., 2011; Wamba et al., 2015; Wang et al., 2015). This involves fundamental changes in the way information is generated and made relevant for organizations (Constantiou and Kallinikos, 2015; Mikalef et al., 2017; Vidgen et al., 2017) and possibly a disengagement from traditional decision theory in a technology-driven context.

Hence, big data cannot be regarded as self-explanatory, as it requires sophisticated techniques from advanced analytics in order to identify valuable insights from vast amounts of noise-affected data (Müller et al., 2016). In this context, analytics as a multidisciplinary concept can be defined as *"(...) the process of introspecting data to discover hidden patterns, meaningful relationships, and interesting associations which can be converted into actionable insights"* (Ramannavar and Sidnal, 2016, p. 294). It comprises manifold techniques from various converging disciplines, such as statistical analysis, mathematical modeling, data mining and machine learning (Chen et al., 2012; Kaisler et al., 2014; Manyika et al., 2011). Depending on the question to be answered and the data given at hand, the complexity of analytical techniques may range from simple tasks, e.g. the exploration of univariate measures, up to more sophisticated tasks, e.g. the identification of non-linear and complex high-level interactions between variables (Ramannavar and Sidnal, 2016). For this reason, different categories of analytics were introduced in order to structure the field along characteristic types of data analysis tasks. Basically, they can be grouped into the three categories descriptive, predictive and prescriptive analytics (Abbasi et al., 2016; Chen et al., 2012; Soltanpoor and Sellis, 2016; Watson, 2014). Some taxonomies even consider a fourth category called diagnostic analytics (Brodsky et al., 2015; Mousannif et al., 2016; Soltanpoor and Sellis, 2016).

Descriptive analytics primarily deals with the questions *"What is happening right now?"* and *"What happened in the past?"*, as it summarizes collected data from various sources and provides aggregated measures and visualizations (Brodsky et al., 2015; Mousannif et al., 2016; Soltanpoor and Sellis, 2016). Furthermore, tools and concepts from traditional business intelligence practice such as reports, dashboards, querying and online analytical processing can be sorted into this category (Delen and Demirkan, 2013; Gluchowski, 2016; Ramannavar and Sidnal, 2016). Diagnostic analytics can be seen as an extension to the descriptive approach, since it tries to answer questions like *"Why did it happen?"* (Soltanpoor and Sellis, 2016). It mainly builds on techniques such as explanatory empirical modeling based on statistical inference and causal hypotheses testing (Brodsky et al., 2015; Mousannif et al., 2016; Shmueli and Koppius, 2011). While descriptive and diagnostics analytics are rather focused on the past, predictive analytics is concerned with a more forward-looking perspective to answer the question *"What is likely to happen?"* (Ramannavar and Sidnal, 2016). The focus is on the development of empirical models that are aimed to deliver predictions with high accuracy (Shmueli and Koppius, 2011). It supports enterprises in identifying potential risks and opportunities by using a large amount of historical data, detecting complex and non-trivial relationships and providing predictions and their equivalent probability scores on new unclassified observations (Soltanpoor and Sellis, 2016). However, extracting insights from the past and the likely future is most often not sufficient. To take advantage of revealed opportunities, it requires to transform valuable insights into actionable recommendations and act upon them in order to meet business objectives (Chen et al., 2012; Kaisler et al., 2014; Soltanpoor and Sellis, 2016). At this point, prescriptive analytics (PA) has emerged as a topic of interest in recent years, which is concerned with the questions *"What should be done?"* and *"Why should it be done?"* (Soltanpoor and Sellis, 2016). It can identify optimal solutions, often connected to allocating scarce resources (Watson, 2014). Though PA has already been studied in academia for a long time (Watson, 2014), there is a broad understanding of which concepts and techniques a prescriptive approach is based on in the current literature about PA. This may range from interpretable prediction models (e.g. decision trees) (Gröger et al., 2014; Mousannif et al., 2016), which deliver actionable rules and recommendations, to expert systems based on different reasoning techniques (Gröger et al., 2014) or optimization approaches built on mathematical modeling (von Bischhoffshausen et al., 2015; Brodsky et al., 2015). Such a conceptual diffusion can lead to an inconsistent understanding about constituent elements for a prescriptive analytics system (PAS) and thus may hinder the development of adequate IS in times when PA is now finding wider use in practice (Watson, 2014). For this reason, the paper deals with a conceptualization of constituent elements of a PAS by conducting a systematic review on existing literature. The goal is to extract fundamental aspects and facets from different perspectives and consolidate them into a coherent view towards a common understanding of a PAS. As such, we define the following research question:

RQ: *What are constituent elements of an IT-based prescriptive analytics system?*

An IT-based PAS is primarily concerned with the task of decision planning and decision-making in the era of digitization. As such, it requires the harmonization of two essential perspectives: On the one hand, the topic is considered from an IS perspective, including aspects related to IT-artifacts within an organizational context (e.g. Benbasat and Zmud, 2003). This is important towards the development of adequate IS (e.g. using adequate information technology, integrating different data sources or automating business workflows) and thus serves as a basis for the conceptualization. On the other hand, it is also necessary to consider the theoretical foundation of decision-making (e.g. de Almeida and Bohoris, 1995) to evaluate well-established concepts in the course of digitization.

Following this approach, the remaining paper is structured as follows: Section 2 depicts the fundamentals of underlying decision theory. Section 3 describes the process of the systematic literature review, summarizes identified research articles and elaborates on the process of conceptualization. In Section 4, an in-depth content analysis is carried out to examine existing definitions of PA and to extract constituent elements of a PAS. Subsequently, in Section 5 the constituent elements are consolidated in a coherent scheme, while a discussion of the results takes place in Section 6. In Section 7, we summarize our findings and provide a brief outlook for further research.

2 Decision Theory as Theoretical Foundation

Before talking about PA as part of organizational decision-making, it is necessary to understand the fundamental aspects of decision theory. Decision Theory has been an active area of research since the 1950s. It provides a logical framework for solving real-life problems and deals with the identification of actions that provide maximum benefits to the decision-maker. Applying decision theory allows to derive the best course of action based on a decision-maker's objectives and knowledge of the problem. The decision-maker can communicate the course of actions and justify why it is optimal. Furthermore, it provides a framework that allows a critical evaluation and modification of the decision-maker's ideas (e.g. when new information is available) (de Almeida and Bohoris, 1995). Decision theorists basically differentiate between two types of decision models (Phillips, 1984): *descriptive models* that tell what decision-makers actually do and *normative models* that are prescriptive and try to explain how decisions should be made (Teale et al., 2002) and what decision-makers should do (Phillips, 1984). Phillips (1984) even adds another type of decision model he calls *requisite models* whose form and content is sufficient, even if not exhaustive, to solve the problem.

According to decision theory the process of decision-making basically involves the following eight ingredients (de Almeida and Bohoris, 1995):

- *Circumstances and basic laws*: The state of nature governing the environment for a particular problem analyzed, not controllable by the decision-maker.
- *Alternatives*: Set of possible actions from which the decision-maker can select a particular course of action.
- *Consequences*: The outcome/pay-off when decision-maker takes a given action in a given set of circumstances, usually expressed in terms of conditional probability.
- *Loss and utility functions*: Quantify the loss or gain incurred from each consequence.
- *Multi-attribute utility theory (MAUT)*: Related to Multi-criteria decision-making, allows the quantification and aggregation of multiple objectives, even when they are composed of conflicting attributes.
- *Elicitation and consistency checking*: Understanding and modelling the preference structure of the decision-maker regarding the consequences.
- *Optimization*: The purpose of decision theory is to obtain an optimum solution to a given problem.
- *Sensitivity analysis*: Investigate the robustness of the solution to the assumptions made.

The extent to which these elements of decision theory are relevant in PAS will be discussed in particular during the conceptualization in Section 4.2, where we bridge the gap to the constituent elements of a PAS as identified in the literature.

3 Research Methodology

We employed a systematic literature review, as it is a firm foundation for advancing knowledge, facilitates theory development and uncovers areas where research is needed. It not only conceptualizes research areas, surveys and synthesizes prior research but also provides an important input for setting directions for future research (Webster and Watson, 2002). As such, in this work it will serve as a basis for a subsequent conceptualization of constituent elements for a PAS. The concepts form clearly defined and interrelated constructs used to present a systematic view of phenomena (Levy and Ellis, 2006), here PAS. We used a two-phase approach for our conceptualization (cf. Figure 1).

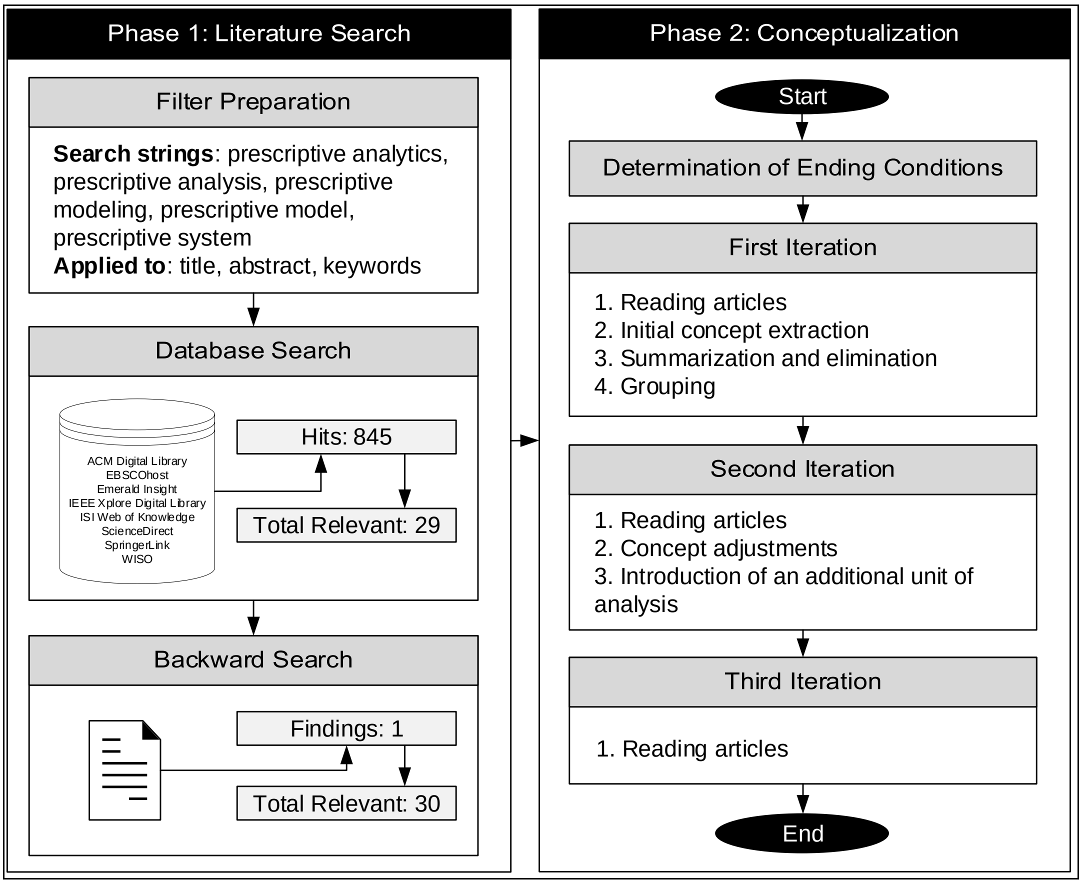

Figure 1. Research Process Overview

3.1 Phase 1: Literature Search

In order to conduct a systematic literature review and identify relevant contributions to answer our research question, we followed the well-recognized guidelines by vom Brocke et al. (2009) and Webster and Watson (2002). The review process was based on a database search using the digital libraries mentioned in Figure 1. For the creation of suitable search strings applying a keyword search, the term 'prescriptive' was concatenated with the terms 'analytics', 'analysis', 'modeling', 'model' and 'system'. Furthermore, the search was limited to the search fields 'title', 'abstract' and 'keywords' whenever such filter mechanisms were provided by the digital libraries. Thus, a total number of 845 hits could be determined (day of search: 2017-08-08). In a next step, this amount had to be further reduced due to duplicates, contributions with limited access and irrelevant content. To ensure the thematic relevance, only search items were kept which directly discuss the concept of PA or address closely related topics, such as big data, business analytics, business intelligence, operations research (OR) or decision support (Voß, 2014). On the other hand, items were explicitly excluded if the search terms were only mentioned but not explained or discussed. At this point, it can be noticed that a significant part of the search results only mentions the term "prescriptive analytics" without specifying characteristics. Thus, the overall amount had to be reduced by 816 items. By conducting a backward search, one additional contribution could be included. Hence, a total number of 30 articles served as a basis for further examination (cf. Figure 1), including 14 journal articles, 12 conference papers and four book chapters.

Considering the dates of publication, the majority was published between 2012 and 2017, except the article of Weber and Coskunoglu (1990) addressing a more theoretical perspective on decision theory and their implications for prescriptive modeling. Considering the type of contributions, the articles can be divided into four non-exclusive categories (cf. Table 1): (i) conceptual discussion with direct focus on PA (4 articles) or (ii) with indirect focus considering umbrella topics such as big data analytics (6 articles), (iii) formal and mathematical discussion towards generic operationalization of PA (5 articles), and (iv) PA application within a specific field of interest (21 articles). In the latter category, most attention is paid on the manufacturing sector (MF, 5 articles), followed by supply chain management (SCM, 3 articles), sales (SA, 3 articles) and academics & research (A&R, 3 articles). The remaining articles belong to other less frequently touched application domains (OTH).

Type of Contribution	Contributions
Conceptual with direct focus on PA	Basu (2013), Shroff et al. (2014), Siksnys (2015), Soltanpoor and Sellis (2016)
Conceptual with indirect focus on PA	Delen and Demirkan (2013), Gluchowski (2016), Mousannif et al. (2016), Ramannavar and Sidnal (2016), Sanjay and Alamma (2016), Schniederjans et al. (2014)
Formal and mathematical discussion	Aref et al. (2015), Lombardi et al. (2017), Shroff et al. (2014), Siksnys (2015), Weber and Coskunoglu (1990)
Application of PA	MF: Abu el Ata and Perks (2014), Brodsky et al. (2015), Gröger et al. (2014), Krumeich et al. (2016), Siksnys (2015) SCM: Heckmann (2016), Matopoulos et al. (2016), Souza (2014) SA: Aref et al. (2015), von Bischhoffshausen et al. (2015), Kawas et al. (2013) A&R: Lee et al. (2014), Soltanpoor and Sellis (2016), Song et al. (2014) OTH: Appelbaum et al. (2017), Ballings et al. (2016), Chalmers et al. (2015), Lavy et al. (2014), Loizou and French (2012), Lombardi et al. (2017), Mendes et al. (2014)

Table 1. Type of contributions of the relevant papers

3.2 Phase 2: Conceptualization

In the second phase, a step by step content analysis of the 30 articles was conducted in order to extract concepts that form the common constituent elements for a PAS. As shown by Webster and Watson (2002) this concept-centric approach in contrast to an author-centric approach rather allows to synthesize the literature than just to present a summary of it. Since the approach we followed was iterative, we defined the following ending conditions based on Nickerson et al. (2013). The process was defined to stop when: (i) no new concept was added (Webster and Watson, 2002), (ii) no concept was changed or (ii) eliminated and (iv) no additional grouping of concepts took place in an iteration.

In a first iteration, each article was read and possible to-be concepts were extracted and added to a concept matrix. Then, for each identified concept duplicates, synonyms and examples where summarized and/or eliminated. Afterwards all concepts extracted were grouped logically (i.e. *input/throughput/output/additional aspects*, cf. Figure 2) and each of the resulting concepts was discussed and if necessary further summarized. In a second iteration of reading the articles, it was checked if the so far identified concepts were in accordance with the articles and suitable generalizations were found. This led to some minor additional summarizations and renaming of concepts. Moreover, an additional unit of analysis was introduced for the first group of concepts. In particular, this refers to the split of the *input* into the two subgroups *decision components* and *origin of data* (cf. Figure 2). Since up to this point the ending conditions were not yet met, a third iteration took place where all articles were checked again. This led to the termination of the process, since no further changes were made to the concept matrix. After conceptualization, the concepts extracted and the insights gained were discussed among the involved researchers and organized in a coherent scheme using focus group methodology as defined by Morgan (1997) (cf. Section 5).

4 Results

In the following, we present the results of the literature analysis by first highlighting a heterogeneous PA understanding and then describing the concepts extracted in the sense of constituent PAS elements.

4.1 Proposed Definitions of Prescriptive Analytics

An initial examination of the 30 articles reveals that they all have a common understanding of PA in the sense, that they consider PA as an IT-based approach for structuring and supporting the process of decision-making in an enterprise context. However, having a deeper look at the elementary level, the approaches differ considerably in their underlying aspects, which can also be demonstrated by different definitions proposed.

For example, many authors consider PA primarily as a mathematical optimization problem, where a decision is determined by optimizing a given business objective (e.g. Brodsky et al., 2015; Kawas et al., 2013; Matopoulos et al., 2016; Song et al., 2014): "*A set of mathematical techniques that computationally determine a set of high-value alternative actions or decisions given a complex set of objectives, requirements, and constraints, with the goal of improving business performance*." (Song et al., 2014, p. 570). Additionally, some authors explicitly emphasize the importance to suggest not only the best course of actions but also their implications in the sense of simulated results (e.g. Lee et al., 2014; Ramannavar and Sidnal, 2016; Siksnys, 2015): "*prescriptive analytics suggests decision options in conjunction with their implications*" (Lee et al., 2014, p. 186) or "*It is purely built on the 'what-if' scenarios*" (Soltanpoor and Sellis, 2016, p. 247).

Moreover, some authors highlight the interplay between PA and predictive analytics, where the results of predictive models deliver an important input for PA (e.g. Basu, 2013; Chalmers et al., 2015; Heckmann, 2016; Krumeich et al., 2016; Soltanpoor and Sellis, 2016): "*Prescriptive analytics uses a computer model to predict the result of each possible action, and then recommends the action giving the best predicted result*." (Chalmers et al., 2015, p. 2).

Another PA approach is pursued by Gröger et al. (2014, p. 34), who developed a rule-based recommendation system using decision trees. They divide the field of PA as follows: "*In general, we observe two types of systems for prescriptive analytics: (1) recommender systems using data mining techniques and (2) expert systems typically using rule-based, case-based and model-based reasoning techniques*."

These examples show that there is a heterogeneous understanding of PA in different domains of application, which results in a variety of aspects and facets to be considered when developing PAS. Thus, the next section aims at creating a common understanding of constituent elements for a PAS independent of the application domain following the methodology described in Section 3.

4.2 Conceptualization of Constituent Elements for a PAS

The extraction and conceptualization was done via a concept matrix as depicted in Figure 2, where it is possible to comprehend which elements are confirmed by which authors (Webster and Watson, 2002). As a result, a total number of 26 concepts could be identified specifying constituent elements for a PAS. During the conceptualization, the field was considered from two perspectives, i.e. an IS point of view for IT-artifact related aspects, on the one hand, and decision theory as theoretical foundation for decision-making processes, on the other hand. The IS perspective served as a basis to structure the concepts derived. As such, we classified the elements for a PAS on a high-level abstraction into "input", "output" and "throughput" according to the system model approach, which is widely used in system theory and information processing (Orr, 1998). This trichotomy could also be found in some papers' definitions of PA (e.g. Delen and Demirkan, 2013). Moreover, a fourth group, called "additional aspects", was added to explicitly consider typical characteristics of IT-artifact within a PAS (e.g. automation, modularization, etc.). Subsequently, after the identification of all concepts, the decision theory perspective was used to relate the concepts extracted to the traditional elements of decision theory as introduced in Section 2. As such, it was possible to examine the extent to which these theoretical elements are relevant in PAS in terms of constituent system elements. In the following, we describe each PAS element in detail (bold letters) and highlight the connection to decision theory (italic letters) whenever it is possible. The subsections are organized in accordance to the four categories proposed above.

	Input											Output				Throughput					Additional Aspects					
	Decision Cmpt.					Origin of Data																				
Contribution	Decision Variables	Objectives	Constraints	Current State	Probabilities	Internal Data	External Data	Assumptions	Empirical Observations	Predictive Results	Descriptive Results	Competing Decisions	Single Decision	Implications	Evaluation	Optimization	Simulation	Heuristics	Interpr. Pred. Models	Expert Systems	Automation	Tracking	Iteration	Time Dependency	Visualization	Modularization
Abul el Ata and Perks (2014)	x				x	x			x	x		x		x			x				x		x	x		
Appelbaum et al. (2017)	x	x	x	x	x	x	x		x	x	x	x	x	x		x	x		x	x	x		x	x	x	
Aref et al. (2015)	x	x	x						x				x			x					x		x			x
Ballings et al. (2016)	x	x	x	x	x		x		x	x			x	x	x	x		x		x			x		x	
Basu (2013)	x	x	x		x	x	x		x	x		x	x	x		x	x			x	x	x	x	x		
Brodsky et al. (2015)	x	x	x	x	x	x			x	x	x	x	x	x		x	x				x					x
Chalmers et al. (2015)	x				x	x			x	x		x	x	x			x									
Delen and Demirkan (2013)	x	x	x					x	x			x	x	x		x	x			x	x					
Gluchowski (2016)	x	x				x	x		x	x	x	x		x												
Gröger et al. (2014)	x				x	x			x	x		x		x					x	x			x	x		
Heckmann (2016)	x	x	x						x			x	x			x	x	x								
Kawas et al. (2013)	x	x	x	x	x	x		x	x	x	x		x		x	x					x					
Krumeich et al. (2016)	x	x	x	x	x	x	x		x	x	x	x	x	x		x	x				x		x	x	x	x
Lavy et al. (2014)	x	x	x	x	x			x	x	x	x	x	x	x	x	x	x									
Lee et al. (2014)	x	x	x	x	x	x	x		x	x	x	x	x	x							x				x	
Loizou and French (2012)	x	x	x	x	x			x	x			x	x	x			x									
Lombardi et al. (2017)	x	x	x		x			x	x	x			x	x	x	x	x	x							x	
Matopoulos et al. (2016)	x	x	x	x	x			x	x		x	x	x	x	x	x	x	x								
Mendes et al. (2014)	x				x		x		x	x		x			x									x		
Mousannif et al. (2016)	x				x	x	x		x	x		x				x			x			x	x			
Ramannavar and Sidnal (2016)	x				x	x	x		x	x		x		x		x	x					x	x	x		
Sanjay and Alamma (2016)	x					x	x		x	x	x		x			x	x	x								
Schniederjans et al. (2014)	x	x	x		x				x	x	x	x	x			x	x	x		x						
Shroff et al. (2014)	x	x	x	x	x	x	x	x	x	x		x	x			x	x	x					x			
Siksnys (2015)	x	x	x	x	x	x	x		x	x	x	x	x	x	x	x	x	x			x			x	x	x
Soltanpoor and Sellis (2016)	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x				x	x	x	x	x	x
Song et al. (2014)	x	x	x	x	x	x	x		x	x	x	x	x	x	x							x	x		x	
Souza (2014)	x	x	x	x	x	x			x	x	x	x	x			x	x	x							x	
von Bischhoffshausen et al. (2015)	x	x	x	x	x	x			x	x	x	x	x	x		x	x				x			x	x	x
Weber and Coskunoglu (1990)	x	x	x	x	x			x					x	x	x	x	x	x		x	x		x			
Σ	30	23	22	16	25	19	14	9	29	24	15	24	24	21	10	22	21	10	3	7	13	5	13	10	10	6

Figure 2. Concept matrix for prescriptive elements

4.2.1 Input

The input describes what is available within a PAS as a basis for data-driven decision-making. Thus, the input part is further subdivided into decision components and concepts that describe the origin of data for those decision components. Both aspects are considered separately in the following.

Decision Components

The decision components refer to the basic elements for structuring a decision problem. According to the conceptualization, they can be further broken down into decision variables, objectives, constraints, current state and probabilities. Here, the strong connection to the fundamental elements of traditional decision theory becomes apparent (Weber and Coskunoglu, 1990; de Almeida and Bohoris, 1995).

Decision variables form the core of a PAS, since they define the object of interest within a decision problem (Matopoulos et al., 2016; Weber and Coskunoglu, 1990). In the sales sector, for example, there is often the problem of sales force assignments, where salesmen, products and clients need to be mapped to each other in a profitable manner (von Bischhoffshausen et al., 2015; Kawas et al., 2013). This triangular relationship can be considered as a decision variable, whose specific values need to be determined. All possible mappings, in this case, form the set of all *alternatives* according to decision theory. The decision variable element can be confirmed by all contributions, even if this explicit term is not used by all authors.

The specification of decision variables in the sense of *alternatives* combined with environmental conditions (i.e. *circumstances and basic laws*) lead to certain states (i.e. *consequences*). These states can be associated with utility values (Weber and Coskunoglu, 1990) (e.g. costs, profit or revenue) and thus are used to measure superior **objectives**, which should be either minimized or maximized (e.g. von Bischhoffshausen et al., 2015; Shroff et al., 2014; Souza, 2014) similar to the *loss and utility functions* in decision theory. Most of the articles state the existence of an objective function, which sometimes is just called objective (e.g. Basu, 2013; Delen and Demirkan, 2013; Lee et al., 2014; Soltanpoor and Sellis, 2016) or optimization function (Krumeich et al., 2016). Objectives can also be composed of multiple, possibly conflicting attributes, where a *multi-attribute utility function* is used instead (Weber and Coskunoglu, 1990). Moreover, there are often **constraints** delimiting the decision space (e.g. Lee et al., 2014; Siksnys, 2015), which can either be limitations given by nature (e.g. workload capacity of a machine (Brodsky et al., 2015)) or strategic requirements (e.g. individual treatment of clients (von Bischhoffshausen et al., 2015)).

As PA tries to express "what should be done", it is also important to know the **current state** of the decision context (i.e. the status quo) and thus decide what should be changed in comparison to this state. Hence, the current state serves as a baseline for evaluating the implications of a decision, e.g. in terms of gains or losses compared to that state (e.g. Matopoulos et al., 2016; Weber and Coskunoglu, 1990). Furthermore, decision problems are usually characterized by some degree of uncertainty. This can be expressed by **probabilities** to indicate how likely a certain outcome is about to happen (e.g. Matopoulos et al., 2016; Soltanpoor and Sellis, 2016). An illustration within the sales example is the likelihood of a distinct product being sold by a salesman to a particular client (von Bischhoffshausen et al., 2015). Probabilities are often directly integrated as weights within the definition of an objective function (e.g. von Bischhoffshausen et al., 2015; Lombardi et al., 2017) and are an essential element when determining the *consequences* of a decision according to decision theory.

Origin of Data

Data used to explicate the decision components comes from different sources. Taking the access to data into consideration allows to distinguish between **internal data**, i.e. data accessed through data bases that are internal to an organization, and **external data**, i.e. data accessed via external data bases and information services. In the sales scenarios, for example, data from internal CRM systems is an essential source of information (von Bischhoffshausen et al., 2015; Kawas et al., 2013). Next to data bases, Appelbaum et al. (2017) name audio, video and sensors as internal data and state news, social media, census and data from the internet of things as external data. They all can be a source of information, for example, for determining decision variables and the current state, defining constraints or calculating probabilities. Some authors do not explicitly distinguish between external and internal but more generally speak of hybrid data (Basu, 2013) or diverse data sources (e.g. Shroff et al., 2014; Siksnys, 2015).

Another aspect of data origin is, how it is generated. From the literature, basically two types of data generation can be distinguished: **assumptions** and **empirical observations**. Whereas empirical observations present real data originating from business process execution (Krumeich et al., 2016), such as historical sales data (von Bischhoffshausen et al., 2015; Kawas et al., 2013), assumptions are hypothetical data created either by human expertise in terms of expert knowledge, experiences and opinions (e.g. Delen and Demirkan, 2013; Kawas et al., 2013; Soltanpoor and Sellis, 2016) or artificially using techniques such as simulation (e.g. Lavy et al., 2014; Lombardi et al., 2017; Matopoulos et al., 2016; Shroff et al., 2014). Again, both types of data can be relevant for defining all decision components.

A third aspect concerning the origin of data is to understand from which of PA's preceding analytical processes it originates, i.e. whether the data represents **descriptive results** like key performance indicators and summary statistics or **predictive results** mainly expressed by probability scores derived from prediction models (Soltanpoor and Sellis, 2016). Descriptive results form a valuable source for defining the current state, whereas predictive results serve as a basis for probability definition. Thus, many authors see descriptive and/or predictive analytics as a necessary foundation for a PAS (e.g. Delen and Demirkan, 2013; Sanjay and Alamma, 2016; Soltanpoor and Sellis, 2016).

4.2.2 Output

The output refers to the actual support of decision-making. Having a decision variable with all its possible specifications (e.g. all possible combinations of salesmen, products and customers in the sales scenario or the set of all *alternatives* in terms of decision theory), there are basically multiple **competing decisions** to choose from. At this stage, several authors emphasize the importance to make the alternatives tangible to the decision-makers and thus improve the transparency within the decision problem (e.g. von Bischhoffshausen et al., 2015; Gluchowski, 2016; Mendes et al., 2014). However, under certain conditions such as costs or resources, it is most often the case, that a **single decision** must be made towards the best suitable solution among all feasible alternatives. At this point, an optimal candidate needs to be determined, an equivalent to the result of *optimization* in decision theory.

Once a decision is made, the corresponding actions need to be taken. Hence, there are **implications**, which reflect (i) certain course(s) of actions, (ii) expected results as well as (iii) associated side effects when making the decision. Thus, the implications concept in PA is more comprehensive than the *consequences* concept in decision theory which it could be associated with. According to several approaches, those implications should also be made transparent to the decision-maker (e.g. Gluchowski, 2016; Krumeich et al., 2016; Lee et al., 2014; Ramannavar and Sidnal, 2016; Soltanpoor and Sellis, 2016), irrespective of whether multiple competing decisions are suitable for a problem or an optimal decision needs to be carried out. Some authors call this aspect of a PA approach what-if-analysis (e.g. von Bischhoffshausen et al., 2015; Lombardi et al., 2017; Soltanpoor and Sellis, 2016). Furthermore, the implications of the decisions taken require an **evaluation** against the input by assessing how the decision components affect the outcome. Some authors, for example, apply sensitivity analysis similar to *sensitivity analysis* in decision theory by comparing the sensitivity of the outcome to input changes (e.g. Kawas et al., 2013; Lavy et al., 2014; Matopoulos et al., 2016).

4.2.3 Throughput

Taking the input and generating output, respectively prescriptions, the literature refers to various techniques and approaches, which can basically be grouped into optimization, simulation, interpretable prediction models, heuristics and expert systems.

The most frequently used approaches are optimization and simulation. The goal of **optimization** techniques is to find the best suitable solution among all possible alternatives in accordance with *optimization* in decision theory. For this purpose, the alternatives of a decision variable, limiting constraints and the objective function are taken into account within a mathematical model and the optimal candidate is determined by maximizing or minimizing the values of the objective function (Matopoulos et al., 2016). Depending on the characteristics and the complexity of the decision problem, various optimization techniques are applicable, like linear programming, integer programming, constraint programming or multi-objective programming (Brodsky et al., 2015; Heckmann, 2016; Matopoulos et al., 2016; Schniederjans et al., 2014). **Simulation**, on the other hand, can help to understand a problem by imitating a system's behavior and analyzing its variation in different situations (Matopoulos et al., 2016). As such, it can be applied for several purposes. For example, to generate additional input data for a prescriptive analytics approach based on reasonable assumptions, in case empirical observations are not sufficient or not even present (e.g. Lavy et al., 2014; Lombardi et al., 2017; Matopoulos et al., 2016; Shroff et al., 2014) or to generate multiple scenarios based on prediction results and conduct what-if-analyses (e.g. von Bischhoffshausen et al., 2015; Lavy et al., 2014; Lombardi et al., 2017; Soltanpoor and Sellis, 2016). Having a number of scenarios investigated, it is also possible to select the candidate showing the best behavior towards an optimal solution (Lombardi et al., 2017). It can be stated, however, that optimization techniques, such as those mentioned above, significantly outperform simulation-based approaches (Brodsky et al., 2015; Lombardi et al., 2017). Furthermore, special simulation techniques, such as Monte Carlo simulation, can even be used for prediction purposes and thus serve as potential input for a prescriptive analytics approach (e.g. Appelbaum et al., 2017; Heckmann, 2016; Loizou and French, 2012; Ramannavar and Sidnal, 2016).

The other prescriptive techniques, i.e. interpretable prediction models, heuristics and expert systems, are only mentioned by a few authors. They are rather of secondary importance, since they overlap to a certain extent with some aforementioned techniques. **Heuristics**, for example, are problem solving techniques based on practical methods to find solutions that are not guaranteed to be optimal but satisfactory for the problem (Heckmann, 2016; Souza, 2014; Weber and Coskunoglu, 1990). A common approach is the use of simplified rules derived from human judgement and experiences of domain experts (Ballings et al., 2016; Lombardi et al., 2017; Shroff et al., 2014). Heuristics are often applied when the process of problem solving is too complex or time-consuming (Souza, 2014), but they also provide valuable baseline models to evaluate the results of advanced optimization techniques (Lombardi et al., 2017). **Interpretable prediction models**, on the other hand, represent a particular type of predictive result. In contrast to typical "blackbox models" (Shmueli and Koppius, 2011), they can deliver actionable insights in terms of rules and recommendations besides the provision of probability scores to evaluate the likelihood of certain outcomes. A prominent example is that of decision trees, which provide human-readable decision rules due to their tree-like structure (Appelbaum et al., 2017; Gröger et al., 2014; Ramannavar and Sidnal, 2016). The last category identified by the literature comprises **expert systems** (e.g. Appelbaum et al., 2017; Delen and Demirkan, 2013), where the decision-making ability of human experts is emulated. A complex problem is being solved by reasoning about knowledge represented by a formalized knowledge base instead of using a truly data-driven approach (Gröger et al., 2014). Accordingly, the use of expert systems in data-intensive environments is currently rather of secondary importance.

4.2.4 Additional Aspects

Besides the definition of input, output and throughput, further concepts could be extracted from the literature, which characterize the nature of a PAS. These are automation, tracking, iteration, time-dependency, visualization and modularization. Conceptualizing only these aspects should not exclude the necessity of further typical IS features when designing PAS but emphasizes their special importance in PA environments.

Many authors see **automation** as an essential constituent. It has to be distinguished between two types of automation: (i) automatically generating decision proposals (e.g. Lee et al., 2014; Song et al., 2014), which still need human-intervention in actually making the decision and conducting the following course of actions (Siksnys, 2015) and (ii) a complete automation of decision-making and the execution of actions as proposed by von Bischhoffshausen et al. (2015), which, for example, is necessary for a continuous process automation without human-intervention in autonomously operating environments such as cyber physical systems (Siksnys, 2015).

The more automation takes place, the more important becomes the **tracking** of actions, which are performed based on the decisions. Therefore, adequate feedback mechanisms for action documentation are necessary (Mousannif et al., 2016; Ramannavar and Sidnal, 2016; Soltanpoor and Sellis, 2016). Based on tracked actions and outcomes, the PAS can **iteratively** adapt to changes due to the implications of the decisions taken (Ballings et al., 2016; Mousannif et al., 2016; Shroff et al., 2014) or adapt to dynamically changed input data, such as updated constraints based on ever-changing environmental factors (Appelbaum et al., 2017; Aref et al., 2015).

Closely related to the dynamics of PAS, another essential element is **time dependency**. Especially within an operational context, decisions often need to be made in real-time (Abu el Ata and Perks, 2014; Mendes et al., 2014) and proactively (Gröger et al., 2014; Krumeich et al., 2016; Soltanpoor and Sellis, 2016) or they are based on real-time data (Appelbaum et al., 2017).

Furthermore, **visualization** could be identified as a crucial element. Even though Ballings et al. (2016) see PAS to eliminate the need for visualization and any subsequent interpretation, the authors themselves employ variable plots to visualize the effectiveness of their prescriptive model. Other contributions employ visualization to present the prescriptive results (e.g. von Bischhoffshausen et al., 2015; Lombardi et al., 2017; Song et al., 2014; Souza, 2014) and Krumeich et al. (2016) even state dashboarding functionalities as a means to not only visualize the final results but all decision-relevant data.

Finally, **modularization** as a typical IS feature is also a fundamental characteristic for PAS, as it helps to reduce the complexity of the system by separating modules for descriptive, predictive and prescriptive functionalities (Soltanpoor and Sellis, 2016). Some examples of modularized PAS can be found in Brodsky et al. (2015), von Bischhoffshausen et al. (2015), Siksnys (2015) and Krumeich et al. (2016).

5 Consolidation into a Coherent View

To summarize our findings and create a common understanding of constituent PAS elements independent from the domain of application, the fundamental aspects and facets described in the previous section are consolidated in a coherent view as illustrated in Figure 3. In the following, the interplay and dependencies between the concepts are briefly described, where we distinguish between artifacts (e.g. *Single Decision*) and processes (e.g. *Iteration*) as part of a PAS.

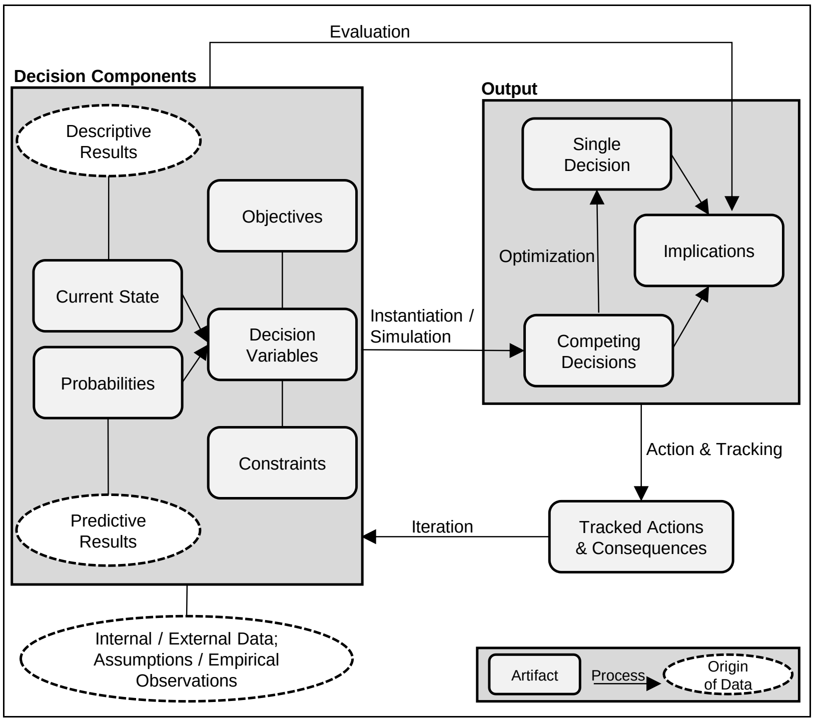

Figure 3. Coherent view of constituent elements for PAS

The central function of a PAS is to support and carry out corporate decision-making. As such, the decision components define the context of the decision problem, encompassing decision variables, objectives, constraints, current state and probabilities. The decision variables are the pivotal element, since they define the decision problem of interest by establishing the relationship between the relevant entities, such as previously demonstrated within the problem of sales force assignments (e.g. von Bischhoffshausen et al., 2015), where salesmen, products and clients need to be mapped to each other. Closely linked to this element are objectives and constraints, as they further restrict the decision space. While objectives set specific targets to be achieved (e.g. maximize revenue), constraints define additional limitations (e.g. only one client per salesman). The current state and probabilities, for their part, can rather be considered as inputs for the use of the decision variables to carry out future decisions. By providing recorded information as well as results of previous decisions (e.g. sales history), the current state reflects the status quo and thus serves as a baseline for evaluation purposes. The probabilities, on the other hand, can be incorporated to indicate the likelihood of certain events to happen (e.g. the likelihood of a distinct product being sold by a salesman to a particular client).

From the data origin point of view, the definition of all decision components may be based on internal or external data, assumptions or empirical observations. On top of that, descriptive results define the current state and probabilities are drawn from predictive results particularly.

Using the decision components and the data characteristics as a starting point for the definition and configuration of the decision problem, it is then the task of the PAS to generate the respective outputs towards the actual step of decision-making. As such, the PAS generates all possible competing decisions, which are allowed within the decision space defined (e.g. all possible mappings between salesmen, products and clients according to specified constraints). This step can be done through pure instantiation, i.e. using values of empirical observations related to the entities of the decision variables (e.g. current availability information about clients, products and salesmen), or by simulating new or so far disregarded values (e.g. simulating mappings for additional, hypothetical employees). If, moreover, given objectives require an optimal solution, suitable optimization techniques need to be applied that lead to a single decision. Regardless of whether a single decision is made or competing decision are proposed by a PAS, they involve implications in the form of necessary course of actions and their side effects. The implications should be evaluated in reference to the decision components by adequate evaluation mechanisms. By tracking the actions performed and their consequences, the decision components might be adjusted in subsequent iterations of the PA process.

The remaining additional aspects identified previously, i.e. automation, time dependency, visualization and modularization, are not explicitly represented within the scheme, since their realization in a PAS strongly depends on the characteristics of the decision problem, the organizational context and the existing IT landscape a PAS is integrated in. The degree of automation, for example, is determined by the availability of decision-relevant data in an adequate form (e.g. machine-readable), the necessity and human acceptance of full-automation within an organization or the interoperability between a PAS and other systems (e.g. via specified interfaces). Nevertheless, they should be considered as important design principles for the purpose of developing adequate PAS as proposed in the previous section.

6 Discussion

In the following, we discuss our results with regard to related work, the contribution of our research approach and implications for practitioners.

Based on the results of the literature review, it can be confirmed that PA is no longer a hypothetical approach, as it is not only increasingly used in practice (Watson, 2014), but also widely discussed within the research community. Existing contributions, for example, position the prescriptive paradigm in broader contexts, such as big data, business analytics or decision support, and in more than 20 articles identified, PA approaches are applied in a variety of application domains (cf. Section 3.1), outlining the merits of a prescriptive scope. However, only a few contributions thoroughly discuss PA with regard to its underlying concepts and their implications for the embedding in adequate IS: While Soltanpoor and Sellis (2016) propose a domain-independent PA framework by describing different components and design elements of a federated architecture, Aref et al. (2015) consider architectural elements from a database perspective, where the authors present a database design based on purely functional data structures to provide built-in support for prescriptive and predictive analytics. Shroff et al. (2014), on the other hand, approach the topic from a mathematical point of view by developing a generic framework that integrates common features of predictive, optimization and simulation models into a unified formal model.

Such an under-representation of studies dealing with the inherent nature of PA and its corresponding embedding in PAS can lead to a conceptual diffusion and terminological proliferation, as demonstrated by a heterogenous set of definitions (cf. Section 4.1). At this point, our work contributes to the field by conceptualizing constituent elements for a PAS and providing a view that is neither limited to any architectural specifications nor to a particular mathematical model, considering the implementation of prescriptive technologies and techniques. Thus, this view can help to get familiar with the essential concepts of an IT-based PAS, while giving enough space and flexibility for further design discussions. In particular, this may help practitioners as a tool for orientation and mediation in requirements engineering during the development of PAS, where a decision problem first should be considered on a generic level, then needs to be transferred to the particular domain of interest with its contextual specifications and subsequently requires the translation into the corresponding infrastructure and application layers. Moreover, the view on constituent PAS elements can be used, for example, to evaluate the comprehensiveness of existing PAS, add additional components, make existing components more explicit or compare and benchmark different types of PAS.

Furthermore, we contribute to the field by bridging the gap between a PA consideration from an IS point of view with regard to aspects relevant for IT-artifacts and a decision theory perspective incorporating the theoretical foundation of decision-making. As such, it could be seen that decision-making in the era of digitization requires an extension of the traditional fundamentals and this paper points out a possible direction how to extend this theory by embedding and translating theoretical decision elements into a technological context towards the establishment of adequate IS. To this end, we have shown that the theoretical constructs themselves are still valid concepts, however, they have to be mapped and integrated into sociotechnical environments in order to satisfy digital requirements for human-to-machine or even machine-to-machine interactions. For example, in PA scenarios the decision-makers are not necessarily human actors, especially when automation plays an evolving important role, and thus human preferences will play a minor role in decision-making as compared to traditional theory. Other requirements at this interdisciplinary core include, for example, visualization of numerous processed information for better interpretability, transparent evaluation mechanism to assess different decision alternatives, tracking of triggered actions for documentation purposes, quick responses to dynamic changes due to fast developing business requirements or the establishment of interfaces to integrate results from predictive and descriptive analytics.

Nevertheless, despite the changes outlined above, our scheme of constituent elements for PAS still allows to implement descriptive, normative (prescriptive) but also requisite decision models in the sense of traditional decision theory. The descriptive nature is realized through integrating the results from descriptive analytics and providing tracking mechanisms. The proposal of (optimal) decisions together with their implications and possibilities for evaluation support normative decision models. Whereas the co-existence of competing decisions with the possibility of evaluation, re-adjustments through iterations and the acceptance of assumptions and simulated data form the foundations for requisite decision models as defined by Phillips (1984).

7 Conclusion and Outlook

In recent years, PA has received much attention as an IT-based approach to structure and support decision-making processes in data-intensive environments. However, as shown in this paper, there is often a broad and multifaceted understanding, which may hinder the development of adequate IS. For this purpose, we proposed a conceptualization based on a systematic literature review, extracted constituent elements of a PAS and consolidated them into a coherent scheme being independent of the application domain.

Our findings can help practitioners and researchers equally to structure the field, get a better understanding of underlying concepts and provide a basis for further developments. Moreover, we have shown a possible direction to bridge the gap between the theoretical foundations of decision theory and aspects that are relevant in digitized, IT-based environments. Thus, the intention is to strengthen the connection between the disciplines of decision science/OR, on the one hand, and IS research/computer science, on the other, which is important to tackle the challenges of data-driven decision-making in complex, dynamic settings (Voß, 2014). In further research, it is planned to use the conceptualization and transfer it into more detailed design proposals for PA architectures and applications, which can be used generically for different decision problems, irrespective of the underlying domain of interest.

References

Abbasi, A., S. Sarker, and R. Chiang (2016). "Big Data Research in Information Systems: Toward an Inclusive Research Agenda." *Journal of the Association for Information Systems* 17 (2), i–xxxii.

Abu el Ata, N. and M. J. Perks (2014). *Solving the Dynamic Complexity Dilemma. Predictive and Prescriptive Business Management: Answering the Need for a New Paradigm*. Berlin Heidelberg. Springer.

Appelbaum, D., A. Kogan, M. Vasarhelyi, and Z. Yan (2017). "Impact of Business Analytics and Enterprise Systems on Managerial Accounting." *International Journal of Accounting Information Systems* 25, 29–44.

Aref, M., B. ten Cate, T. J. Green, B. Kimelfeld, D. Olteanu, E. Pasalic, T. L. Veldhuizen, and G. Washburn (2015). "Design and Implementation of the LogicBlox System." In: *Proceedings of the 2015 ACM SIGMOD International Conference on Management of Data, SIGMOD '15*. ACM. New York: NY, USA, pp. 1371–1382.

Ballings, M., D. Van den Poel, and M. Bogaert (2016). "Social Media Optimization: Identifying an Optimal Strategy for Increasing Network Size on Facebook." *Omega* 59, 15–25.

Basu, A. (2013). "Five Pillars of Prescriptive Analytics Success." *Analytics Magazine (March/April 2013)*. 8–12.

Benbasat, I. and R. W. Zmud (2003). "The Identity Crisis within the IS Discipline: Defining and Communicating the Discipline's Core Properties." *MIS Quarterly* 27 (2), 183–194.

Brodsky, A., G. Shao, M. Krishnamoorthy, A. Narayanan, D. Menascé, and R. Ak (2015). "Analysis and Optimization in Smart Manufacturing based on a Reusable Knowledge Base for Process Performance Models." In: *2015 IEEE International Conference on Big Data*. Santa Clara: CA, USA, pp. 1418–1427.

Chalmers, E., D. Hill, V. Zhao, and E. Lou (2015). "Prescriptive Analytics Applied to Brace Treatment for AIS: A Pilot Demonstration." *Scoliosis* 10 (2), 1–4.

Chen, H., R. H. L. Chiang, and V. C. Storey (2012). "Business Intelligence And Analytics: From Big Data To Big Impact." *MIS Quarterly* 36 (4), 1165–1188.

Constantiou, I. D. and J. Kallinikos (2015). "New Games, New Rules: Big Data and the Changing Context of Strategy." *Journal of Information Technology* 30 (1), 44–57.

de Almeida, A. T. and G. A. Bohoris (1995). "Decision Theory in Maintenance Decision Making." *Journal of Quality in Maintenance Engineering* 1 (1), 39–45.

De Mauro, A., M. Greco, and M. Grimaldi (2015). "What is Big Data? A Consensual Definition and a Review of Key Research Topics." In: *AIP Conference Proceedings* 1644 (1), pp. 97–104.

Delen, D. and H. Demirkan (2013). "Data, Information and Analytics as Services." *Decision Support Systems* 55 (1), 359–363.

Gluchowski, P. (2016). "Business Analytics – Grundlagen, Methoden und Einsatzpotenziale." *HMD Praxis der Wirtschaftsinformatik* 53 (3), 273–286.

Gröger, C., H. Schwarz, and B. Mitschang (2014). "Prescriptive Analytics for Recommendation-Based Business Process Optimization." In: *Business Information Systems (BIS). Lecture Notes in Business Information Processing*. Ed. by W. Abramowicz, A. Kokkinaki. Springer, Cham, pp. 25–37.

Heckmann, I. (2016). "Supply Chain Risk Analytics." In: *Towards Supply Chain Risk Analytics*. Springer Gabler. Wiesbaden, pp. 131–162.

Kaisler, S. H., J. A. Espinosa, F. Armour, and W. H. Money (2014). "Advanced Analytics – Issues and Challenges in a Global Environment." In: *Proceedings of the 47th Hawaii International Conference on System Sciences*. Waikoloa: HI, USA, pp. 729–738.

Kawas, B., M. S. Squillante, D. Subramanian, and K. R. Varshney (2013). "Prescriptive Analytics for Allocating Sales Teams to Opportunities." In: *IEEE 13th International Conference on Data Mining Workshops*. Dallas: TX, USA, pp. 211–218.

Krumeich, J., D. Werth, and P. Loos (2016). "Prescriptive Control of Business Processes." *Business & Information Systems Engineering* 58 (4), 261–280.

Lavy, S., J. Garcia, P. Scinto, and M. Dixit (2014). "Key Performance Indicators for Facility Performance Assessment: Simulation of Core Indicators." *Construction Management and Economics* 32 (12), 1183–1204.

Lee, M., M. Cho, J. Gim, D. H. Jeong, and H. Jung (2014). "Prescriptive Analytics System for Scholar Research Performance Enhancement." In: *International Conference on Human-Computer Interaction (HCI) - Posters' Extended Abstracts*. Communications in Computer and Information Science. Springer, Cham, pp. 186–190.

Levy, Y. and T. Ellis (2006). "A Systems Approach to Conduct an Effective Literature Review in Support of Information Systems Research." *Informing Science: The International Journal of an Emerging Transdiscipline* 9, 181–212.

Loizou, P. and N. French (2012). "Risk and Uncertainty in Development: A Critical Evaluation of Using the Monte Carlo Simulation Method as a Decision Tool in Real Estate Development Projects." *Journal of Property Investment & Finance* 30 (2), 198–210.

Lombardi, M., M. Milano, and A. Bartolini (2017). "Empirical Decision Model Learning." *Artificial Intelligence* 244, 343–367.

Manyika, J., M. Chui, B. Brown, J. Bughin, R. Dobbs, C. Roxburgh, and A. H. Byers (2011). *Big Data: The Next Frontier for Innovation, Competition, and Productivity*. Report. McKinsey Global Institute.

Matopoulos, A., J. E. Bell, and E. Aktas (2016). "The Use of Modelling in Purchasing/Supply Management Research." *Journal of Purchasing and Supply Management* 22 (4), 262–265.

Mendes, P. N., D. Gruhl, C. Drews, C. Kau, N. Lewis, M. Nagarajan, A. Alba, and S. Welch (2014). "Sonora: A Prescriptive Model for Message Authoring on Twitter" In: *Web Information Systems Engineering*. Lecture Notes in Computer Science. Springer, Cham, pp. 17–31.

Mikalef, P., I. O. Pappas, J. Krogstie, and M. Giannakos (2017). „Big Data Analytics Capabilities: A Systematic Literature Review and Research Agenda." *Information Systems and e-Business Management*, 1–32.

Morgan, D. (1997). *Focus Groups as Qualitative Research*. 2nd Edition. Thousand Oaks, California: USA. Qualitative Research Methods.

Mousannif, H., H. Sabah, Y. Douiji, and Y. Oulad Sayad (2016). "Big Data Projects: Just Jump Right In!" *International Journal of Pervasive Computing and Communications* 12, 260–288.

Müller, O., I. Junglas, J. vom Brocke, and S. Debortoli (2016). "Utilizing Big Data Analytics for Information Systems Research: Challenges, Promises and Guidelines." *European Journal of Information Systems* 25 (4), 289–302.

Nickerson, R. C., U. Varshney, and J. Muntermann (2013). "A Method for Taxonomy Development and its Application in Information Systems." *European Journal of Information System*s 22 (3), 336–359.

Orr, K. (1998). "Data Quality and Systems Theory." *Communications of the ACM* 41 (2), 66–71.

Phillips, L. D. (1984). "A Theory of Requisite Decision Models." *Acta Psychologica* 56 (1), 29–48.

Ramannavar, M. and N. S. Sidnal (2016). "Big Data and Analytics – A Journey Through Basic Concepts to Research Issues." In: *Proceedings of the International Conference on Soft Computing Systems, Advances in Intelligent Systems and Computing*. Springer. New Delhi, pp. 291–306.

Sanjay, M. and B. H. Alamma (2016). "An Insight into Big Data Analytics - Methods and Application." In: *International Conference on Inventive Computation Technologies (ICICT)*. Coimbatore, pp. 1–5.

Schniederjans, M. J., D. G. Schniederjans, and C. M. Starkey (2014). *Business Analytics Principles, Concepts, and Applications with SAS: What, Why, and How*. Pearson Education.

Shmueli, G. and O. R. Koppius (2011). "Predictive Analytics in Information Systems Research.*" MIS Quarterly* 35 (3), 553–572.

Shroff, G., P. Agarwal, K. Singh, A. H. Kazmi, S. Shah, and A. Sardeshmukh (2014). "Prescriptive Information Fusion." In: *17th International Conference on Information Fusion (FUSION)*. Salamanca, pp. 1–8.

Siksnys, L. (2015). "Towards Prescriptive Analytics in Cyber-Physical Systems." PhD Thesis. Technical University Dresden and Aalborg Universitet.

Soltanpoor, R. and T. Sellis (2016). "Prescriptive Analytics for Big Data." In: *Databases Theory and Applications*. Lecture Notes in Computer Science. Springer, Cham, pp. 245–256.

Song, S., D. H. Jeong, J. Kim, M. Hwang, J. Gim, and H. Jung (2014). "Research Advising System Based on Prescriptive Analytics." In: *Future Information Technology*. Lecture Notes in Electrical Engineering. Springer, Berlin, Heidelberg, pp. 569–574.

Souza, G. C. (2014). "Supply Chain Analytics." *Business Horizons* 57 (5), 595–605.

Teale, M., V. Dispenza, J. Flynn, and D. Currie (2002). *Management Decision Making: Towards an Integrative Approach*. Harlow: Financial Times/Prentice Hall.

Vidgen, R., S. Shaw, and D. B. Grant (2017). "Management Challenges in Creating Value from Business Analytics." *European Journal of Operational Research* 261 (2), 626–639.

vom Brocke, J., A. Simons, B. Niehaves, K. Riemer, R. Plattfaut, and A. Cleven (2009). "Reconstructing the Giant: On the Importance of Rigour in Documenting the Literature Search Process." In: *Proceedings of the 17th European Conference on Information Systems (ECIS)*. Verona: Italy, pp. 2206–2217.

von Bischhoffshausen, J. K., M. Paatsch, M. Reuter, G. Satzger, and H. Fromm (2015). "An Information System for Sales Team Assignments Utilizing Predictive and Prescriptive Analytics." In: *IEEE 17th Conference on Business Informatics.* Lisbon: Portugal, pp. 68–76.

Voß, S. (2014). "Interview with Daniel Dolk and Christer Carlsson on "Decision Analytics."" *Business & Information Systems Engineering* 6, 181–184.

Wamba, S. F., S. Akter, A. Edwards, G. Chopin, and D. Gnanzou (2015). "How "Big Data" Can Make Big Impact: Findings from a Systematic Review and a Longitudinal Case Study." *International Journal of Production Economics* 165, 234–246.

Wang, X., L. White, and X. Chen (2015). "Big Data Research for the Knowledge Economy: Past, Present, and Future." *Industrial Management & Data Systems* 115 (9).

Watson, H. (2014). "Tutorial: Big Data Analytics: Concepts, Technologies, and Applications." *Communications of the Association for Information Systems* 34 (1), 1247–1268.

Weber, E. U. and O. Coskunoglu (1990). "Descriptive and Prescriptive Models of Decision-Making: Implications for the Development of Decision Aids." *IEEE Transactions on Systems, Man, and Cybernetics* 20 (2), 310–317.

Webster, J. and R. T. Watson (2002). "Analyzing the Past to Prepare for the Future: Writing a Literature Review." *MIS Quarterly* 26 (2), xiii–xxiii.

Zschech P., K. Heinrich, M. Pfitzner, and A. Hilbert (2017). "Are You Up for the Challenge? Towards the Development of a Big Data Capability Assessment Model." In: *Proceedings of the 25th European Conference on Information Systems (ECIS)*. Guimarães: Portugal, pp. 2613–2624.