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VALUE CO-CREATION AND POTENTIAL BENEFITS THROUGH BIG DATA ANALYTICS: HEALTH BENEFIT ANALYSIS

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ABBREVIATIONS

AI	Artificial intelligence
BDET	Big data analytics-enabled transformation
CDS	Clinical decision support
EBMeDS	Evidence-Based Medicine Electronic Decision Support
EHR	Electronic health record
EMR	Electronic medical record
IS	Information system
IT	Information technology
GPS	Global positioning system
HBA	Health Benefit Analysis
ML	Machine learning
NNT	Number needed to treat
ODA	Self Care and Digital Value Services
PHR	Personal health record
PTB	Potential to benefit
RFID	Radio frequency identification
SAMK	Satakunta University of Applied Sciences
STAR	Socio technical allocation of resources
TUT	Tampere University of Technology

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ABSTRACT

Big data analytics in healthcare context is often studied from a technical point of view. In the field of strategic management, researchers have indicated a research gap in how big data analytics create business value. This study examines how big data and advanced analytics generate potential benefits and business value for the healthcare service provider, and value for the individual patients and population health. In addition, the effects of advanced analytics to the value co-creation practices and actors in healthcare ecosystem are studied. The theoretical framework used for the purpose is the big data analytics-enabled transformation model which is adapted to answer the research questions. The study is conducted as a single case study. The studied case is the Health Benefit Analysis (HBA) tool. The empirical data is collected in eight semi-structured interviews with participants of the tool development project.

Using the HBA tool reveals several paths-to-value chains. The most evident path shows how using advanced analytics affects the personalized care practice by enabling a more interactive service process between the health professionals and patients. It denotes a business scope redefinition as patients are now being interpreted as essential actors in the value co-creation of their own health outcomes. The benefits that arise from the advanced analytics are of several dimensions; operational, managerial, strategic, and organizational. Using the HBA tool generates strategic business value for the healthcare service provider as a differentiator that contributes to gaining competitive advantage compared to other service providers not using this innovation. Value emerges for the individual patient as improved patient experience and better health outcomes. Population health gains most value from the reduced health inequalities.

The evolving value co-creation practices set requirements for the healthcare ecosystem actors as they need to conform to new practices with patients and other professionals from other sectors and levels of the ecosystem. The healthcare work and service culture need to develop and adapt to new tools, related processes, and a more diversified professional base, including health analysts and other new professionals. To conclude, it can be claimed that advanced analytics of healthcare big data contributes to the shift to value-based healthcare.

KEYWORDS: value co-creation, big data analytics, value-based healthcare, health benefit analysis, healthcare ecosystem.

1. INTRODUCTION

Digitalization has rapidly become reality for many industries by disrupting old business models. New and enhanced value co-creation practices yield possibilities to offer increased value and various potential benefits for the business owners, individual customers, and entire customer segments. Digital transformation has also had its effect and changed the way of thinking and way of working in the healthcare industry. This change is still ongoing, and the development of digital healthcare services, related medical products and equipment, as well as the electronic information systems in the field, continue to evolve in the future.

1.1. Background of the study

According to Barlow (2016: 3, 13), the medical knowledge base is growing exponentially, since more data is collected about the patients and new medical information is published every day, which no single human being can keep up with, leading to a situation where doctors and other care staff need help to succeed with this highly complex field of life sciences. According to Obermeyer & Lee (2017: 1209), every patient is a “big data” challenge, as medical knowledge is expanding rapidly, and patients are older with more coexisting illnesses and medications. Further, Barlow (2016: 1 – 3) claims that the traditional labor-intensive healthcare transforms into more knowledge-driven and data-intensive practice where the newer healthcare delivery models depend on user-friendly, real-time big data analytics, artificial intelligence (AI) and machine learning (ML) tools, and that millions of individual patients may benefit from the improved capabilities on diagnosis and treatments. Also, according to Rose and Burgin (2014: 11), real-time big data analytics has the potential to enable well-timed interventions to get customers, i.e. patients the right care, at the right time, and in the right venue. This, in turn narrows the potential gaps in healthcare delivery, and in that means, generates potential savings by improving the operating conditions, as well as competitiveness of the healthcare service providers. The improved capabilities can become an asset on population level as well, for example with disease management and epidemics tracking, such as hotspots of Malaria, or by providing estimations of influenza activity as Google Flu Trends does (Sahay 2016: 420, 426; Raghupathi & Raghupathi 2014: 8). Moreover, it can help with ensuring the needed proactive care delivery and interventions for specific groups of patients suffering from similar health problems, e.g. heart failure or hypertension (Kunnamo 2017).

To become one of the game changers and to contribute to the discussion, healthcare service providers should invest in investigating the value and potential benefits of big data and advanced analytics, for example how data analytics could enhance the offered healthcare services and ensure that these services optimally meet the patients' needs and improve their health condition. From a business development point of view, it should be evaluated how the use of advanced analytics can create value for the actors in the healthcare ecosystem, as well as for the end customers, i.e. the specific populations and individual patients.

Regarding the development of information technology in healthcare (E-Health) in the European Union, scholars have indicated some inequalities between the member states, as many of them, usually the richest ones, have been able to invest more in the development, while some countries have not. Therefore, the European Council urged in 2013 for the reduction of the digital gap in healthcare amongst the member states. (Quaglio, Dario, Stafylas, Tiik, McCormack, Zilgalvis, D'Angelantonio, Karapiperis, Saccavini, Kaili, Bertinato, Bowis, Currie & Hoerbst 2016: 314). The European Union (2016) also carried out a systematic literature review and consultation of experts to identify examples of the use and value of big data analytics in the practice of public healthcare and telemedicine, and to identify whether there is a need for policy recommendations to develop and support the use of big data in public health. This review also confirms that the increasing availability of data and technical progress combined with limited financial resources, stakeholders in public health as well as the scientific community are open to the opportunities offered by big data applications not only for the health of the individual but also for the health of the whole population. Moreover, the review indicates that the use of big data might improve also the performance and outcome of healthcare systems. (European Union 2016: 22, 25.)

The most important lesson the European Union (2016: 55) learned in its review was that raising awareness of the added value of big data in health is needed quite urgently by stimulating a continuous open dialogue with all stakeholders and patient groups. Consequently, the public discussion around the major potential benefits and challenges of big data in health is in full flow and will continue in the coming years.

In order to achieve any potential benefits and expected value from advanced and big data analytics, there are, however, many challenges on the way. These issues need to be studied and answered to, which makes the effects of data analytics to value co-creation practices in the field of healthcare an interesting research topic. Moreover, according to McKinsey & Company reports (Manyika, Chui, Bughin, Dobbs, Bisson & Marrs 2013: 11) big data applied with disruptive technologies like Internet of Things, cloud, next generation genomics, and advanced robotics, are expected to increase significantly and become a trillion-dollar business by 2025. It is also estimated to reduce healthcare spend in US of $300 billion to $450 billion (Groves, Kayyali, Knott, Van Kuiken 2013: 8 – 9). Big data is of great significance in optimizing the costs of public and private health systems, and it also promotes healthy lifestyles and activities, helping people to avoid chronic diseases (Chen, Ma, Song, Lai & Hu 2016: 830), so it definitely pays off to resolve as many challenges as possible in the years to come.

1.2. Research gap

Studies have indicated that there are challenges with matching the capacity of healthcare units with the need of care of patients, which requires to develop systems that increases the accessibility for care and better match the supply and demand (Nordgren 2011: 304). Such systems can be considered as platforms for value co-creation opportunities for healthcare service providers and healthcare consumers, referred to as patients (Andrews, Sahama & Gajanayke 2014: 375). Moreover, the study of Andrews et al. (2014: 378 – 379) indicates some promising effects caused and value created by using digital resources in healthcare service setting. Therefore, there is demand for additional studies regarding value co-creation models of digital healthcare services. Bardhan and Thouin (2013: 447) also indicate the importance of examining the information technology enabled capabilities and the impact of these capabilities on the process and quality outcomes in order to explain how benefits can be derived from adapting information technology in healthcare.

To gain further understanding of the nature and scope of value co-creation, Lusch, Vargo & Gustafsson (2016: 2060 – 2961) conclude in their research on transdisciplinary service ecosystems, that more opportunities to study service ecosystems based on digital platforms, including for example computer and information sciences, should be considered. This makes sense, since such service ecosystems involve in value co-creation not only human actors, but also organizational and digital artifacts. According to Storbacka, Brodie, Böhmann, Maglio & Nenonen (2016: 3008), actor engagement as microfoundation for value co-creation has become a major research stream in strategic management, as it is empirically more observable than value co-creation itself. Storbacka et al. (2016: 3013) indicate several research gaps related to actor engagement, one particularly concerning the role of machine actors, for example advanced algorithms which are predicted to play a much bigger role in service ecosystems in the future.

According to Demirkan, Bess, Spohrer, Rayes, Allen & Moghaddam (2015: 734) big data is a business priority that has the potential to change the competitive landscape of today's globally integrated economy by providing innovative solutions and new ways to transform processes, organizations, entire industries, and even society. However, the research of big data and big data analytics have so far concentrated mostly on the technical side, whereas the business value, as well as managerial and strategic views especially in the field of healthcare has not yet been sufficiently explored (Wang, Kung & Byrd 2016: 1; Sivarajah, Kamal, Irani & Weerakkody 2017: 279 – 280; Wang & Hajli 2017: 295). Uncovering the potential value and benefits for various stakeholders, governments need to invest time, resources, visioning, and planning on how to successfully implement big data technologies (Archenaa & Mary Anita 2015: 313) and in future research on how recent advancements on information technology and big data analytics systems can be effectively exploited in healthcare services (Sakr & Elgammal 2016: 57).

1.3. Objectives and research questions

Value co-creation practices have a major role in how value is created. Since the digitalization has its effect in value co-creation practices and involved actors, and because the research of the value of advanced data analytics and big data analytics in healthcare industry is lagging compared to other industries, it is worth to conduct a research on this topic. Thus, the objective of this study is to discover how using big data and advanced analytics create potential benefits for healthcare service providers and consumers, i.e. the specific populations and individual patients, and how it affects in value co-creation practices in the healthcare ecosystem.

These research objectives are studied by answering to the following research questions:

RQ 1. *How does big data and advanced analytics generate potential benefits and value for healthcare service providers, individual patients, and population health?*

RQ 2. *How does big data and advanced analytics affect the value co-creation practices and actors in a healthcare ecosystem?*

Finding out how big data and advanced analytics create value and benefits for various stakeholders, contributes the healthcare service organizers and providers to indicate and analyze potential care gaps and plan how to narrow the deficits by optimizing healthcare services timely and cost-effectively for those patients who benefit most from them.

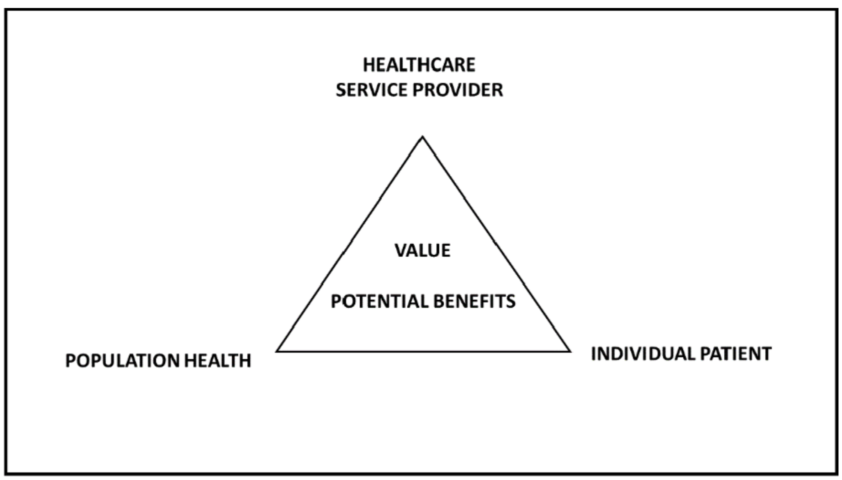

Figure 1. Three perspectives to potential benefits and value.

Specifically, the study is concentrated on the potential benefits and value that arise from introducing advanced analytics of healthcare big data as an actor in the value co-creation practices. The value is viewed from three perspectives; the healthcare service provider's, population health's and individual patient's (Figure 1). The study discusses also how advanced analytics affects the value co-creation practices and respective actors in the healthcare ecosystem. It is also possible to identify new types of actors emerging in the healthcare ecosystem due to the use of big data and advanced analytics. This may provide insights for management in how to develop its resources and needed competencies.

The theoretical contribution of this study fills in the stated gap in research of the impact of big data analytics in the field of healthcare, using the concept of value co-creation from the discipline of strategic management. Also, the theoretical framework used for analyzing the paths-to-value chains and specific benefit dimensions, which is primarily intended for revealing the business value of big data analytics solely from the healthcare service organizer's or provider's perspective, will be extended so that it also sheds light on the potential benefits for individual patients and population health. The managerial implications include the affected value co-creation practices which need to be considered when planning to introduce advanced analytics or big data analytics in healthcare context. Moreover, the discovered potential benefits for the stated stakeholders are presented, and a summary of identified challenges and opportunities are discussed.

1.4. Thesis structure

The thesis first introduces the background to the topic and discusses the potential areas of research interests and needs in the field, explains research objectives, and presents the research questions. The second chapter introduces the context of the study that is value-based healthcare through health benefit analysis, as well as discusses the characteristics of individual and population health management. The literature review covers the concepts and principles of value, value co-creation, service systems, as well all as characteristics of typical co-creation practices and actors in a healthcare ecosystem. The theoretical part continues with discussing big data and big data analytics. Last, the framework for analyzing the value and potential benefits of big data analytics is introduced and extended to cover not only the business value, but also the value for population health and individual patients.

The theoretical part is followed by the methodology, which introduces the used research method and explains the background and reasons why that method was selected. Also, the collection, handling and analyzing methods of the empirical data is explained in detail. Finally, in the results chapter the case is introduced, and the results of the analyzed empirical data is reported. The results are compared to the theory, which is the base for conclusions. The conclusions consist of key findings, theoretical and managerial implications, as well as ideas for future research.

2. DATA-DRIVEN VALUE CO-CREATION IN HEALTHCARE

This chapter first introduces the context of the study, i.e. information technology (IT) enabled value-based healthcare through health benefit and care gap analyses. It also describes the purpose and target groups of the analyses, as well as discusses briefly the users, that primarily are professionals representing various healthcare service providers.

Further, it introduces through literature review the characteristics of value and value co-creation, related service logics, as well as discusses how co-creation practices and actors are perceived in healthcare ecosystems, and raises the potential impact of digital actors, e.g. data analytics and algorithms as value co-creators. The chapter continues with introducing the concept of big data and advanced analytics, especially in the healthcare context. Finally, the theoretical framework for studying the effects and potential benefits through advanced data analytics, on which the health benefit analysis is based, is presented. The framework used for the purpose is the 'big data analytics-enabled transformation model', which includes selected organizational IT-enabled practices treated and examined in this study as value co-creation practices. The model includes also specific benefit dimensions, which are explored not only from the business value point of view, but also to find out what kind of value propositions it creates for individual patients and population health management. Therefore, specifically for this study, an applied version of the big data analytics-enabled model is developed and introduced.

2.1. Value-based healthcare

Healthcare is often perceived as expensive and inefficient. Moreover, healthcare service delivery outcomes are of varied quality. Therefore, there is room for improvement and need for changing the focus of how success of healthcare is measured. Instead of monitoring healthcare efficiency with the number of patient visits or number of performed tests and procedures, the interest should be in the effectiveness of medical and care interventions, for example on quicker patient recoveries, fewer readmissions to the hospital, lower infection rates, and fewer medical errors. In other words, healthcare should be valued by its outcomes, which is referred to as *value-based healthcare*. The goal of value-based healthcare is to lower the healthcare costs and improve the quality and outcomes of healthcare service delivery.

(Cosgrove 2013.) Porter & Teisberg (2006: 4 – 5, 155) argue that the primary goal of each healthcare provider must be excellence in patient value. They also agree with that value of healthcare can only be measured over the care cycle, not by individual procedures, services, office visits or tests, and raise a concern about the fact that among doctors there is a lack of overall perspective on the care-cycle, and that navigating in the care-cycle is challenging for patients. Therefore, they suggest paying attention to current practices and test how they contribute to creating value for the patients, instead of focusing on short term costs and battling over who pays what. Moreover, Porter & Teisberg (2006: 8) claim that value-based competition among healthcare service providers cuts out the inefficiency and quality problems that plague healthcare services and motivates the poorly performing service providers to improvement.

Porter (2010: 2477 – 2478) has also argued that achieving value for patients should be the overarching goal of healthcare delivery. Further, value in healthcare is created by the health outcomes which can be evaluated on individual patient or population level. The goal is what matters for patients and unites the interest of all actors in the system. Value should also define the framework for performance improvement in healthcare delivery.

Shifting the focus to value-based healthcare means that healthcare service providers must solve a challenging puzzle, because they are expected to reduce variation in quality and produce improved outcomes at lower costs. However, this can be viewed as an opportunity for development. For example, value-based care teams can be established, unnecessary practice variation can be eliminated by developing evidence-based care paths across diseases, comprehensive care coordination can be improved so that patients move seamlessly through the system, as well as unnecessary visits in health centers and hospitalizations can be reduced. (Cosgrove 2013.) In order to develop more qualified and value-based healthcare services, information technology platforms and data-driven solutions play a major role (Cosgrove 2013; Barlow 2016: 1 – 3). One possibility to improve the value of healthcare for individual patients and specific populations, is to perform health benefit analyses in order to target the interventions and care for those in need, and for those who would gain most benefit out of them.

2.1.1. Health benefit analysis and care gap

Health benefit analysis and *care gap*, are two central concepts to understand when discussing the health impact of the outcomes of specific interventions. The health benefit analysis has according to Kunnamo & Alper (2017) two phases: determining the care gap and calculating the health benefit of filling the gap.

According to Kunnamo & Alper (2017: 2 – 3) The *health benefit analysis for an individual* is a list of net impacts of different interventions. For the patient, a health impact can be considered as a benefit or a harm. The net benefit or harm of an intervention is the sum of net impact of all its outcomes. Further, *"the health benefit is the net benefit of an intervention, which is calculated by subtracting the sum of all important harms from the sum of all important benefits".* On individual level, health benefit analysis acts as a tool for making a care plan and shared decisions between the patient and the doctor when making choices between alternative interventions (Kunnamo & Alper 2017: 3). The freedom of choice regarding the interventions creates value for the patient and means that the doctor and patient are practicing shared decision-making which differs from the traditional situation where doctor is responsible for the decision-making and risk-bearing when deciding which interventions are most beneficial and impactful for the patient's health. (McGuire, Henderson & Mooney 1988: 39, 46, 48; Jung & Padman 2015: 302). However, it is often claimed that patient is deemed to be in an asymmetric relation to healthcare providers and thus incapable of making purposeful choices based on sufficient knowledge, as well as that in case the doctor fails to give patients information about alternative interventions, the patients possibility to choose is strongly impaired (Nordgren 2011: 309). In this respect, the health benefit analysis seems to be promising.

On the population level, the health benefit analysis helps the healthcare service providers to allocate resources for medical services and interventions that provide the largest health benefit for the population in the most cost-effective manner. Thus, the *health benefit analysis for a population* is a *care gap analysis* listing how many people would benefit from each intervention complemented by numbers that indicate the average health impact of each intervention. (Kunnamo & Alper 2017: 3 – 4.) Such innovative use of advanced analytics is comparable to other innovative internet technologies which can be valuable for underserved populations as with this technology care providers can reach patients who otherwise would not have access to healthcare service they could benefit from (Jung & Padman 2015: 299 – 300). Practical examples of the described health benefit analyses (Kunnamo & Alper 2017) are presented in Appendix 1.

The concept of care gap in healthcare context seems often to be related to a specific medical condition or population, such as patients with heart disease, children, women, the elderly, or an ethnic group. A general definition of a care gap, provided by The Free Medical Dictionary (2017), according to which health care gap is "*a disparity between healthcare needs, and the healthcare services, especially as it applies to the medically indigent*". This definition supports the concept of health and well-being gap which Sitra (2017) describes being the care gap between the needs of an individual patient and the healthcare services offered or available for the individual patient or a group or a population of similar patients. The gaps can also be caused by patient's hidden needs which currently can be found only randomly when the patient is visiting a doctor for another reason. Care gap analysis, as well as the plans how to implement it, are also discussed by Lehto and Neittaanmäki (2017: 19 – 21) in their report regarding the Finnish health data environment. However, they do not provide any comprehensive definition to the care gap or care gap analysis concepts, therefore the concepts and definitions provided by Kunnamo & Alper (2017) and Sitra (2016) are applied accordingly in this study.

2.1.2. Individual patient's and population health management

An individual person's health and wellbeing depends on many factors, such as the person's overall health condition, living and health behavior habits. In cases of sudden illness or long-term illness, the person becomes a patient, or a consumer of healthcare services run by public or private healthcare providers. The *individual patient* is treated with interventions ordered or recommended by doctors and healthcare professionals. The recommended interventions and treatments are based on the medical professionals' expertise and assessments on what would be the most beneficial for the patient's health. In addition, to get well, or improve their health condition, the patients also themselves have to take responsibility for their care with following the recommendations and possibly make some changes in their lifestyle. According to Batalden, Batalden, Margolis, Seid, Armstrong, Opipari-Arrigan & Hartung (2016: 509), in such situation health outcomes, in good and bad, are co-produced between doctor and patient, and emphasize the importance of effective communication so that a shared understanding of the problem and mutually acceptable care plan can be created. This is supported also with the empirical evidence on that informed and activated patients may be effective in facilitating good health outcomes at lower cost (Batalden et al. 2016: 509).

Porter (2010: 2478) argues, that value for an individual patient is created by providing combined efforts over the full cycle of care and that benefits, and outcomes of care depend on how successfully the practices and interventions are integrated. However, according to Health Level Seven International[1] (2013: 6 – 7), care planning and coordination of care delivery over time and across multiple settings and disciplines has long challenged the healthcare community due to the complexity of chronic conditions, increased number of interventions, and care across multiple sites. Therefore, it recommends healthcare service providers to use digital and standardized integrated care plans, which cover all conditions and treatments of an individual patient. Also, Nordgren (2009: 124) points out the importance of care coordination in order to avoid ineffective use of healthcare capacity and staff, decreased accessibility and long waiting periods to healthcare, as well as the risk of offering inadequate care for an individual patient.

Population health has been defined in literature in different ways, because it is, according to Kindig (2007: 139 – 140), a relatively new term and there has not been agreement whether it refers to the concept of health or to the field of study of health determinants. Therefore, Kindig and Stoddart (2003) and Kindig (2007) have studied the concept thoroughly to be able to provide a suggestion for how to determine population health and how to define the concepts related closely to it. As a result, they define population health as "*the health outcomes of a group of individuals, including the distribution of such outcomes within the group*" (Kindig & Stoddart 2003: 381; Kindig 2007: 143).

Some authors have chosen other viewpoints to define population health, and for example Dunn and Hayes (1997: S7) in their turn determine population health as "*the health of a population as measured by health status indicators and as influenced by social, economic, and physical environments, personal health practices, individual capacity and coping skills,*

[1] Health Level Seven International (HL7, http://www.hl7.org/) is a not-for-profit, ANSI-accredited standard developing organization dedicated to providing a comprehensive framework and related standards for the exchange, integration, sharing, and retrieval of electronic health information that supports clinical practice and the management, delivery, and evaluation of health services.

human biology, early childhood development, and health services". (Kindig 2007: 143 – 145.)

Population health outcomes are discussed extensively in the literature as well, and for example Kindig (2007: 148) provides a definition for the outcomes as "*all possible results that may stem from exposure to a causal factor from preventive or therapeutic interventions; all identified changes in health status arising as a consequence of the handling of a health problem*". Further, health outcome measures can be classified for example to mortality rate, morbidity, disability, health status, and quality of life.

Evans and Stoddart (1990) define population health outcomes and their distribution in the population with specific health determinants such as social environment (e.g. income, education occupation), physical environment (e.g. clean air and water, urban design of neighborhoods), genetic endowment, individual response (behavior/habits and biology), health care (access, quantity and quality of health care services), disease, health and function, well-being, and prosperity. (Kindig 2007: 153.)

According to Kindig (2007: 142), population refers to a group of individuals, in contrast to the individuals themselves, organized into many different units of analysis, depending on the purpose of the research. A population can be for example a geographic region, nation, community or a group of employees, disabled persons, or ethnic groups (Kindig & Stoddart 2003: 381).

To create value and by that means benefit for the whole society, healthcare organizations need, as their core responsibility, to improve the health of populations and individual patients' experience of care, but at the same time also reduce the cost per capita of healthcare (Kindig & Isham 2014: 7). Triple Aim, framework developed by Institute for Healthcare Improvement[2], is a contemporary concept striving to fulfill the mentioned three aspects. Kindig & Isham (2014: 3) propose, that the Triple Aim framework is complemented by developing a specific multisectoral community health business partnership model, which they claim to be even better for achieving the goals.

[2] The Institute for Healthcare Improvement (IHI, http://www.ihi.org/), an independent not-for-profit organization based in Cambridge, Massachusetts, is a leading innovator, convener, partner, and driver of results in health and health care improvement worldwide.

However, a common challenge for healthcare systems funded through taxation, regardless how it is organized, is to decide what services to offer and to whom, within a limited budget (Airoldi, Morton, Smith & Bevan 2014: 965). This may cause inequalities among local population of a healthcare center, as some patients are offered interventions they need, and due to several reasons, some are not. Some patients may be even unnecessarily over-treated. To ensure that interventions are delivered in equal manner, and to provide a tool for the local health planners in their annual task of allocating fixed budgets to a wide range of types of healthcare and improve population health in a specific geographical area, Airoldi et al. (2014: 965) have developed a model for socio technical allocation of resources (STAR) including a value-for-money triangle (Figure 2), which can be used for evaluating the cost-effectiveness of interventions and expected benefits, as well as how to improve population health and reduce possible inequalities among population.

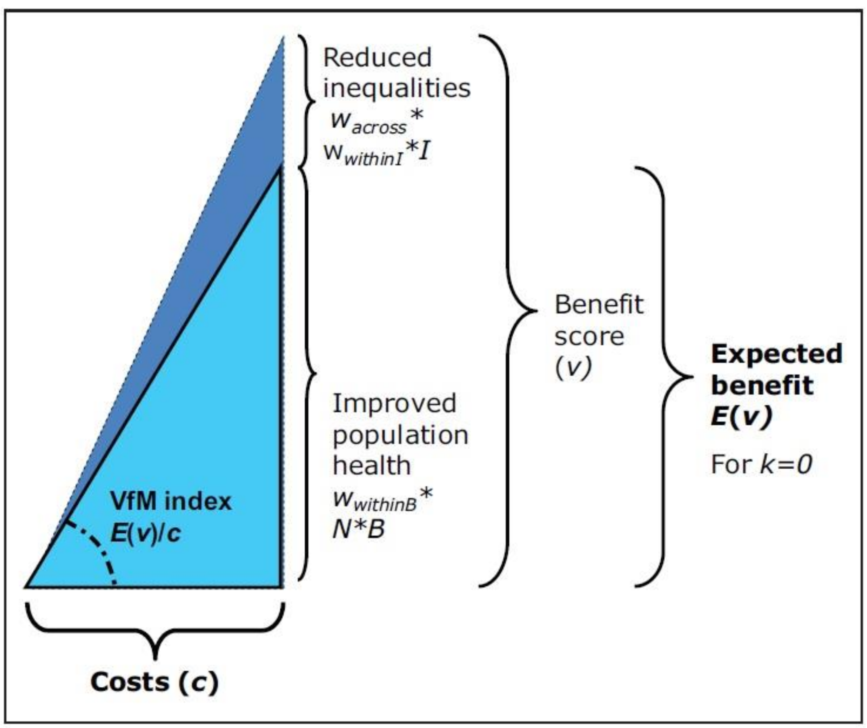

Figure 2. The structure of a value for money triangle.

The horizontal side of the triangle represents the cost associated with the intervention. The vertical side represents the additional expected benefit score. The larger the triangle, the larger the health benefit in the population. The higher the triangle, the more cost-effective intervention. Additional benefit can be gained from reduction of health inequality. (Airoldi et al. 2014: 970; Kunnamo 2016: 69.)

To conclude, value-based healthcare concentrates on the effectiveness of interventions and treatments and is measured by health outcomes and improvements in patient's health instead of the number of single visits in health centers. On population level, practicing value-based healthcare provides an opportunity to cost-effectiveness and reduction of health inequalities among patients. Various analytical methods, such as health benefit analyses can be used to reach the underserved patients and populations. The earlier the needed interventions are implemented, the better and more cost-effective health outcomes.

2.2. Value and value co-creation in service systems

Creation of value has traditionally been the core purpose and central process of economic exchange (Vargo, Maglio & Akaka 2008: 145). Regarding value and value co-creation, there are several recurring concepts which need to be explained and defined, in order to be able to understand and discuss the opinions on the characteristics of value co-creation presented by a number of researchers. Therefore, in this subsection, these concepts and related service logics and systems are introduced and discussed. Further, the value co-creation practices and service ecosystems are presented in the context of healthcare.

2.2.1. Concept of value

Although it is difficult to define and measure, *value* for customers, according to Grönroos (2008: 303), means that after a customer has been assisted by a self-service process or a full-service process, he or she feels better off than before. For example, in successful healthcare service delivery, where the outcome has improved an individual patient's health, value has been created for the customer. Also, Rantala & Karjaluoto (2016: 34) suggest that in the healthcare sector, the definition of value and value offering is based on the betterment of the patient's condition. Sometimes value can be measured in financial terms, sometimes it can be indicated through effects on revenues or wealth or gained through cost savings. Value is considered to have also an attitudinal component such as trust, affection, comfort, and easiness of use. In some cases, value can also be negative. (Grönroos 2008: 303.)

Value and the nature of it has been debated already in the ancient times as in the 4th century B.C. Aristotle distinguished value into use value and exchange value in order to address the difference between things and their attributes. *Use value*, or v*alue-in-use* refers to collection of substances or things and the qualities associated with these, whereas *exchange value*, or *value-in-exchange* has been more difficult to explain. In contemporary research value-in-exchange is referred to as goods-dominant (G-D) logic and exemplified with how value is created in the form of goods, e.g. an automobile, which is exchanged in the marketplace for money. (Vargo et al. 2008: 146.)

Grönroos (2008: 298, 304) expresses his views on the issue with "*when customers are using resources they have purchased, value is created as value-in-use"*, and continues with a statement that is "*value-in-exchange in essence concerns resources used as a value foundation which are aimed at facilitating customers' fulfilment of value-in-use*", and draws a theoretical conclusion according to which value-in-exchange can exist only if value-in-use can be created.

Further, Grönroos (2008: 298) claims that when value is viewed from the value-in-use perspective, the customers are regarded as the value creators. When a service provider adopts a service logic which enables its involvement in the customer's value-generating processes, the service provider can become a co-creator of value with its customers. Hence, *value co-creation* is a value generating process carried out in interaction between the supplier or service provider and the customer.

Some scholars refer to the value co-creation phenomenon with different terminology. For example, Osborne, Radnor and Nasi (2012: 139) have studied service-dominant approach in public management and agree with that service is an intangible process in which production and consumption occur simultaneously, and where users are obligate co-producers of the outcome. Co-production as a term, however, characterizes more the goods-dominant logic which refers to transformation of raw materials into sellable goods.

Vargo et al. (2008: 145) define value co-creation as a phenomenon where value is created collaboratively in interactive configurations of mutual exchange and refer to these configurations as service systems. Moreover, it is stated that the service systems and value co-creation are studied within a discipline called service science.

2.2.2. Service science and service-dominant (S-D) logic

In this study, the business value and potential benefits of big data analytics are studied in the field of healthcare. To learn how the healthcare services are arranged and how healthcare works, the interaction between healthcare service providers, patients and other possible actors can be explored. *Service science* is the study of service systems and of value co-creation within complex constellations of integrated resources. A *service system* is an arrangement of resources, such as people, competences, technology (e.g. algorithm) and information (derived from data) connected to other systems by value propositions. The purpose of a service system is to make use of its own resources to improve its circumstances and enhance that of others. In service systems, value is defined in terms of improvement in system well-being. In other words, value is not created until the well-being of a customer has improved in some way. (Vargo et al. 2008: 145, 149 – 150.) The definition of service science is applicable when examining healthcare service arrangements consisting of populations and patients as customers, and for example health centers with their professionals, equipment and supporting information systems as service providers.

According to Vargo et al. (2008: 145), *service* is determined as the application of competences, such as knowledge and skills. In addition, Grönroos (2008: 300), brings into focus the fact that service can be viewed from three aspects, stating first that service is an activity, a process where someone does something to assist someone else, and then examining service from customer's perspective as value creation, and from service providers perspective as business logic. Further, Grönroos (2008: 299) separates the service logic from customer's and service provider's perspectives in the following way:

> "1. When using resources provided by a firm together with other resources and applying skills held by them, customers create value for themselves in their everyday practices (customer service logic).

2. When creating interactive contacts with customers during their use of goods and services, the firm develops opportunities to co-create value with them and for them (provider service logic)."

Service-dominant (S-D) logic, developed and introduced by Vargo et al. (2008), emerged when the traditional goods-dominant models of value creation concentrating only on firm's output and price were challenged with new alternative perspectives. S-D logic is characterized with the notion of value co-creation that suggests that there is no value until an offering is used, and that the customer always need to participate in value co-creation (Vargo et al. 2008: 148). Grönroos (2011: 282 – 283) has however challenged this view of S-D logic and argues that the value creating activities of the service provider and customer cannot be included in the same analysis, and suggests that the service provider's value creation is an all-encompassing process which is separate from the customer's creation of value-in-use. Further, in case there is a mutual value-in-use creation between the service provider and customer, Grönroos (2011: 290 – 291) insists that it happens in "*one merged coordinated interactive process*", and states that "*if there are no direct interactions, no value co-creation is possible*".

Interestingly, Rantala & Karjaluoto (2016: 34) agree with the definition of value co-creation where both parties create mutual value via cooperation, but also address the new mode of interaction in value co-creation as the digitization of the services is transforming the scene. The idea that value can be created only in direct interaction, is challenged as digitization of services has changed the traditional service-process thinking and technology has enabled both parties to act independently and not necessarily simultaneously (Rantala & Karjaluoto 2016: 36). The new ways of interaction in value co-creation through digital platforms transforms value co-creation according to Rantala & Karjaluoto (2016: 40) so remarkably, that they suggest a paradigm shift in definitions of interaction and time-dependency.

As indicated, the exploration of value co-creation has over the years raised lively debate among scholars. Thus, the definitions of it as well as the determining factors of S-D logic have now been encapsulated by Vargo & Lusch (2017: 47) and Lusch et al. (2016: 2957) in form of five axioms:

" 1. Service is the fundamental basis of exchange
2. Value is co-created by multiple actors, always including beneficiary

3. All social and economic actors are resource integrators
4. Value is always uniquely and phenomenologically determined by the beneficiary
5. Value co-creation is coordinated through actor-generated institutions and institutional arrangements".

Conclusively it can be argued, that in a service situation, value is co-created rather than created and delivered by one actor, and that the S-D logic represents a dynamic continuing narrative of value co-creation through resource integration and service exchange (Vargo & Lusch 2017: 47). Moreover, since the S-D logic represents a dynamic and continuing narrative of value co-creation, it has increasingly been introduced to new disciplines, such as data analytics and cognitive computing. Also, the continued research of value co-creation has resulted in studies where various service ecosystems have become more frequent units of analysis for value co-creation, for example in healthcare. (Vargo & Lusch 2017: 47, 58, 62.)

2.2.3. Healthcare ecosystem and value co-creation practices

Ecosystems are, in biological literature, defined as communities of organisms interacting over time and space with other organisms and other elements in the system. Markets, economies, and similar human systems are comparable with natural ecosystems because they change and emerge similarly over time. Interestingly, to capture this systemic dynamism, S-D logic has identified the concept of *service ecosystem*. (Lusch et al. 2016: 2958.)

A service ecosystem is defined by Lusch et al. (2016: 2958) as "*a relatively self-contained, self-adjusting system of resource-integrating actors connected by shared institutional arrangements and mutual value creation through service exchange*". Moreover, when the five axioms of the S-D logic are coupled with the concept of service ecosystem, Vargo & Lusch (2016) formulate the process of value co-creation in the following way (Lusch et al. 2016: 2958):

> "Value co-creation occurs through (social and economic) actors, involved in resource integration and service exchange, enabled and constrained by institutions and institutional arrangements, establishing nested and interlocking service ecosystems of value co-creation, which serve as the context for future value co-creation activities."

As indicated in Figure 3, *healthcare ecosystem* consists of multiple levels and actors being more complex than a relationship between solely a doctor and patient (Frow et al. 2016: 27). The healthcare ecosystem is divided into four levels each consisting of various actors, such as people and organizations. The mega level involves government agencies defining the aspects of health policy, while on macro level e.g. state health authorities determine the allocation of funding. On meso level operate the hospitals and local health support agencies, and on micro level the co-creation practices involve doctors, nurses, and patients with their families. (Frow et al. 2016: 27.)

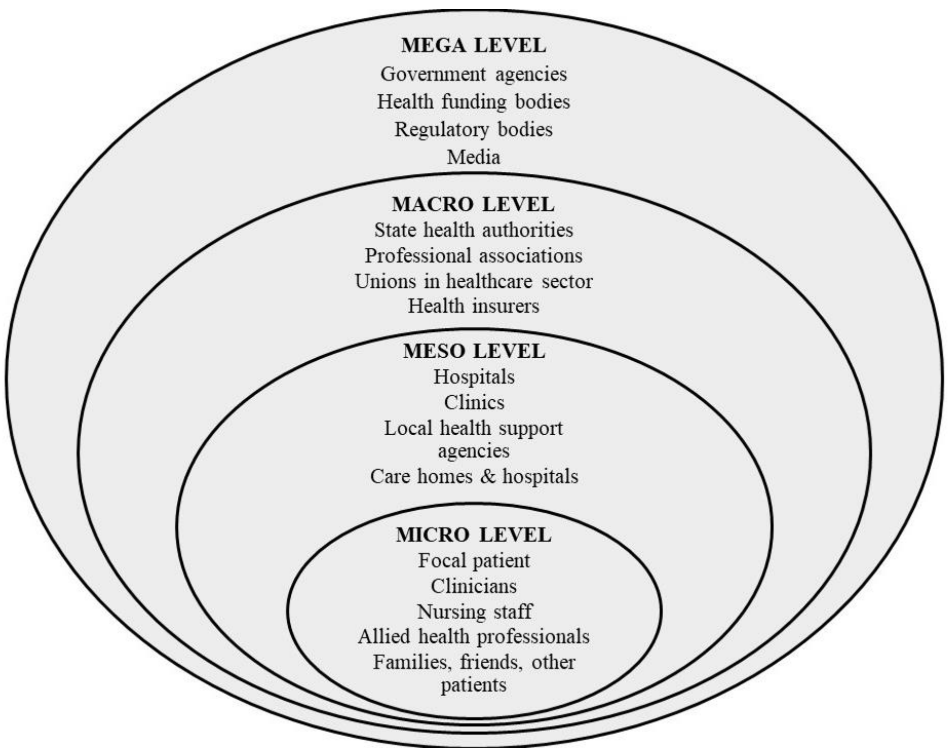

Figure 3. Healthcare ecosystem (adapted from Frow et al. 2016: 27).

As stated, the broader mega level issues concern mostly the policies set by the national governments. In this context, the ongoing healthcare reform in Finland can be addressed. According to the current political debate, the governmental actors on the mega level suggest that after the reform is implemented, there will be a new actor on the macro level responsible for organizing the healthcare service, and on the meso level, there will be public and private healthcare service providers.

Value co-creation practice is a resource integration process which involves actors sharing their resources during collaborative activities and interactions. For example, sharing resources such as electronic health records between hospitals and health centers results in more informed and relevant treatment for patients. The important role of practices is to link the actors within an ecosystem, as well as realize benefits for the actors and ensure the well-being of the service ecosystem, and finally for the benefit of the patient. (Frow, McColl-Kennedy & Payne 2016: 24, 26.)

One purpose of the study by Frow et al. (2016: 30) was to identify and create a typology of co-creation practices in the field of healthcare and analyze whether the impact of the identified practices can be considered as positive or negative. They identified altogether eight co-creation practices (Table 1) that support the ecosystem well-being. This study highlights practices CP3, CP5, CP6 and CP7, because they might be positively impacted when health benefit analyses (cf. subsection 2.1.1.) are used as part of healthcare services.

Table 1. Typology of co-creation practices and their indicative measures in healthcare (Frow et al. 2016: 31 – 33).

Co-creation practices	**Examples of indicative measures**
CP1: Practices that endow actors with social capital	Density or volume of interactions Degree of bonding, bridging, and linking actors Actor proximity in direct or intermediated interaction
CP2: Practices that provide an ecosystem with shared language, symbols, signs and stories	Extent that dissemination of symbols, signs and stories within ecosystem Extent of use/dissemination of symbols, signs and stories
CP3: Practices that shape an actor’s mental model	Change in co-creation practices/behavior/activities Change in actors’ worldview of their role within the whole ecosystem

	Extent of adoption of customer-centered practices (e.g. patient-centered care model)
CP4: Practices that impact the ecosystem, created or constrained by the physical structures and institutions that form their contexts	The extent to which rules, norms, and procedures change over time together with their impact How changes to a structure or institution impact existing practices and support new practices
CP5: Practices that shape existing value propositions and inspire new ones	Extent of actor perceived change in focus or in direction of value proposition Articulation of new propositions Extent to which existing and new value propositions follow best-practice guidelines
CP6: Practices that impact access to resources within an ecosystem	Extent to which actors offer access opportunities and platforms for resource sharing Extent to which resources are shared by all actors within an ecosystem
CP7: Practices that forge new relationships, generating interactive and/or experiential opportunities	Extent to which practices create opportunities for forging new relationships within the ecosystem Extent to which actors engage in new co-creation practices Extent, strength and intensity of relationships within ecosystem
CP8: Practices that are intentionally co-destructive creating imbalance within the ecosystem	Defection of actors from the ecosystem The growth of new ecosystems that supersede original ecosystem Extent of conflicting roles of actors who belong to multiple ecosystems

In addition, patients can also become active co-creators for their own health services when they are given more responsibility for maintaining their own health for example by eating healthier foods, exercising, and practicing self-care (Nordgren 2009: 121). However, there has been claims that patients are deemed to be in asymmetric position in relation to the healthcare providers, and thus incapable of making proper choices based on sufficient knowledge (Nordgren 2011: 309). In practice, according to Nordgren (2011: 309), there is a lack of system, which informs patients of the available options in terms of treatments, as well as risks and quality, and doctors fail to give patients information about alternative treatments on regular basis which lead to situations where the patients' possibilities to choose are strongly impaired. Hence, as suggested by Frow et al. (2016: 32), practices that inspire new value propositions, may solve the problem in form of e.g. health benefit analysis.

Further, Payne, Storbacka & Frow (2008: 93 – 94) suggest that professionals can even teach the patients certain value co-creation behaviors by for example communicating expectations on how patients can actively participate in the co-creation of value. This can be compared to a situation where healthcare professional suggests a patient to stop smoking as an intervention to improve his health condition. If patient agrees and acts as suggested, value co-creation can be claimed to happen.

Frow et al. (2016: 35) argue, that value co-creation practices have a central role in shaping an ecosystem, and that the co-creation practices they identified are especially relevant to healthcare and to the emerging trend toward putting the patient at the center of processes and structures related to their well-being. Again, in the context of the Finnish healthcare reform, the plan is, that on the micro level, the patient-centered approach will be in focus, thus providing the patient a freedom of choice regarding the healthcare service provider.

Regardless of the national setup of the healthcare ecosystem, within it there are multiple interactions that occur with each level and across levels. Many actors are also involved directly and indirectly, within and across these ecosystem levels. (Frow et al. 2016: 28.)

Besides that, Payne et al. (2008: 83, 88) agree with the discussion regarding the service science theme by arguing that the key feature of the service-dominant (S-D) logic is that the customer becomes a co-creator of value, they add that value co-creation through technological breakthroughs and innovative services offer new ways for service providers to engage customers in co-creation of value and customer experiences. For example, a healthcare service provider can engage patients in their own care and decision making related to it by offering services via new technology, digital platforms or through data-driven solutions.

2.2.4. IT-enabled and data-driven value co-creation

According to Storbacka et al. (2016: 3010), the value co-creating actors in an ecosystem can be humans or a collection of humans, such as organizations, but if limiting the view only on human actors, the impact of technologies is ignored. However, service ecosystems are increasingly dependent on technology. Technological advancements in information technology (IT), such as digitization of services in various disciplines provide significant opportunities to study how it impacts the actors in an ecosystem, not only human but also other natural and artificial elements such as algorithms, and their interactions within the service ecosystem, for example in the field of healthcare. (Lusch et al. 2016: 2960.)

Information technology enables the effective coordination of healthcare services, improve patient management, and play a key role in expanding access to healthcare services as it helps with connecting patients and health professionals, as well as provides patients an opportunity to act as active partners in their treatment (Quaglio et al. 2016: 314). For example, the use of electronic health records (EHR) and proving patients access to their own records, as well as embedding decision support tools in EHR systems have reportedly generated positive impacts on healthcare quality and better healthcare process quality (Bardhan & Thouin 2013: 439).

Demirkan et al. (2015: 734) agree by arguing that IT enables organizations to improve their inter- and intra-organizational collaboration, effectiveness, efficiency, and innovativeness by facilitating new types of services and creating possibilities for value co-creation with consumers, i.e. patients in the case of healthcare services. For example, a healthcare service provider can enable value co-creation with patients by providing an online booking system, telemedicine services, as well as improve effectiveness by sharing electronic health records among healthcare providers (Andrews et al. 2014: 376).

According to Groves et al. (2013: 7), introducing big data in the service ecosystem in healthcare may be even changing the paradigm, as it enables the creation of feedback loop which keeps patients informed, provides opportunity to evidence-based care and selecting appropriate care provider, leads to sustainable approaches continuously enhancing healthcare value in form of cost reductions at the same or better quality, as well as provides opportunity for innovation. Consequently, according to Storbacka et al. (2016: 3010) the entities in such ecosystems are collections of arrangements of resources, including people, organizations, technology and information, e.g. big data, and advanced analytics of it.

To conclude, in service ecosystems value is co-created in interaction between various actors. In health ecosystem, there are specific value co-creation practices that can be identified and evaluated how they are affected or transformed when in addition to the digital actors, such as advanced analytics, is introduced in the ecosystem.

2.3. Big data

In information technology, data is the source of information and knowledge. The value of it lies in its use, which varies over time, place, and context. If data is in isolation, it has no meaning or value. Data can be of wide range of value, but it is often found only long after it has been collected and organized, or the value of it is understood only after it is lost. (Borgman 2015: 3 – 4.) Since 1990s, companies have been storing large volumes of data (Delen 2014: 232), and the amount of collected and stored data from various sources in multiple formats has increased exponentially, which has led to the rise of the concept of big data (Demirkan et al. 2015: 735). Regarding the value of big data, it has been compared to oil of modern business and the glue of collaboration. It is expected to reveal the hidden treasures in the bit streams of life. (Borgman 2015: 3). To uncover the value of big data to healthcare, Archenaa & Mary Anita (2015: 407 – 408) recommend also governments to harness it for use in order to improve quality and minimizing the costs, and to enable value-based healthcare for patients.

2.3.1. Definitions of big data

Big data means different things to different people, and traditionally the term has been used to describe massive volumes of data analyzed by huge organizations such as Google or research science projects at NASA (Delen 2014: 231; Demirkan et al. 2015: 734). In healthcare, according to the European Union (2016: 11), big data refers to large routinely or automatically collected datasets, which are electronically captured and stored. It is reusable in the sense of multipurpose data and comprises the fusion and connection of existing databases for the purpose of improving health and health system performance. It does not refer to data collected for a specific study.

The dimensions of big data are in the literature often defined with varying number of *big data V's*. For example, IBM data scientists (2017) break big data into four V's: volume – scale of data, velocity – analysis of streaming data, variety – different forms of data, and veracity – uncertainty of data. Gartner (2017a) in turn, characterize big data the V's being high in nature, e.g. high-volume, high-velocity and/or high-variety information assets that demand cost-effective, innovative forms of information processing that enable enhanced insight, decision making, and process automation.

As the number of V's and characteristics of big data presented in the literature are variedly defined, a summary of the V's and respective definitions or described characteristics are presented in Table 2.

Table 2. Summary of the seven big data V's definitions and characteristics.

Big data 'V'	Definition / Characteristics	Source
Volume	Large amounts of data	Berman (2013: xx)
	Refers to the scale and the size of data	Sakr & Elgammal (2016: 50)
	The data comes in large amounts	Sahay (2016: 420)
Velocity	The content of the data is constantly changing, through the absorption of complementary data collections, through the introduction of previously archived data or legacy collections, and from streamed data arriving from multiple sources	Berman (2013: xx)
	Represents the streaming data and large-volume data movements	Sakr & Elgammal (2016: 50)
	Concerns data in motion/streaming data, bandwidth, and how fast data is being produced and how fast it must be processed to meet the needs/demands	Demirkan et al. (2015: 735)
	The data has a real-time and continuous nature	Sahay (2016: 420)

Variety / Variability	The data comes in different forms, including traditional databases, images, documents, and complex records	Berman (2013: xx)
	Refers to the complexity of data in many different structures	Sakr & Elgammal (2016: 50)
	Concerns data's many forms (i.e. structured, unstructured, text, multimedia, video, audio, sensor data, meter data, html and so on)	Demirkan et al. (2015: 735)
	The data (structured and unstructured) have different sources	Sahay (2016: 420)
Veracity	Concerns data in doubt, e.g. uncertainty due to data inconsistency and incompleteness, ambiguities, latency, deception, accuracy, quality, truthfulness, or trustworthiness of data	Demirkan et al. (2015: 735)
	The data can be triangulated from multiple sources	Sahay (2016: 420)
Validity	The data reflects primary sources of collection	Sahay (2016: 420)
Volatility	The data is available over time	Sahay (2016: 420)
Value	Potential of big data to be utilized for development	United Nations Global Pulse (2013: 2)
	Concerns data for co-creation, the relative importance of data to the decision-making process	Demirkan et al. (2015: 735)
	The *use value* of big data represents how it helps to address problems and use conditions, while the *exchange value* of big data represents its reusable intellectual capital and how it is used in multiple contexts to generate value	Sahay (2016: 421)

Berman (2013: xx) emphasizes that it is important to distinguish big data from ‘massive data’ or ‘lots of data’, and claims that at least volume, variety, and velocity of the V’s must apply in order to fulfill the definition of big data.

Delen (2014: 237) claims that velocity may be the most overlooked characteristics of big data, but too important to be ignored as when data is created it starts to age and degrade and its value proposition becomes worthless, for example, in healthcare, the capability to access and process patient data quickly creates more advantageous outcomes for the patient. Raghupathi & Raghupathi (2014: 10) agree with this by arguing that real-time big data analytics is a key requirement in healthcare. Delen (2014: 238) continues by stating that the excitement around big data is created by its value proposition, which promises that by analyzing large and feature-rich data, organizations can gain greater business value than they could by detecting patterns in small datasets or by using simple statistical methods and concludes with statement “*big data means big analytics*”.

The origin of big data is versatile (IIHT 2013: 6), and according to Delen (2014: 232) big data comes from everywhere. As the three-level diagram in Figure 4 depicts, variety and velocity, as well as volume of data increases when the traditional databases are first complemented with mostly human-generated complicated data from the internet and social media and grows even more when machine and sensor generated data is added to the big data set.

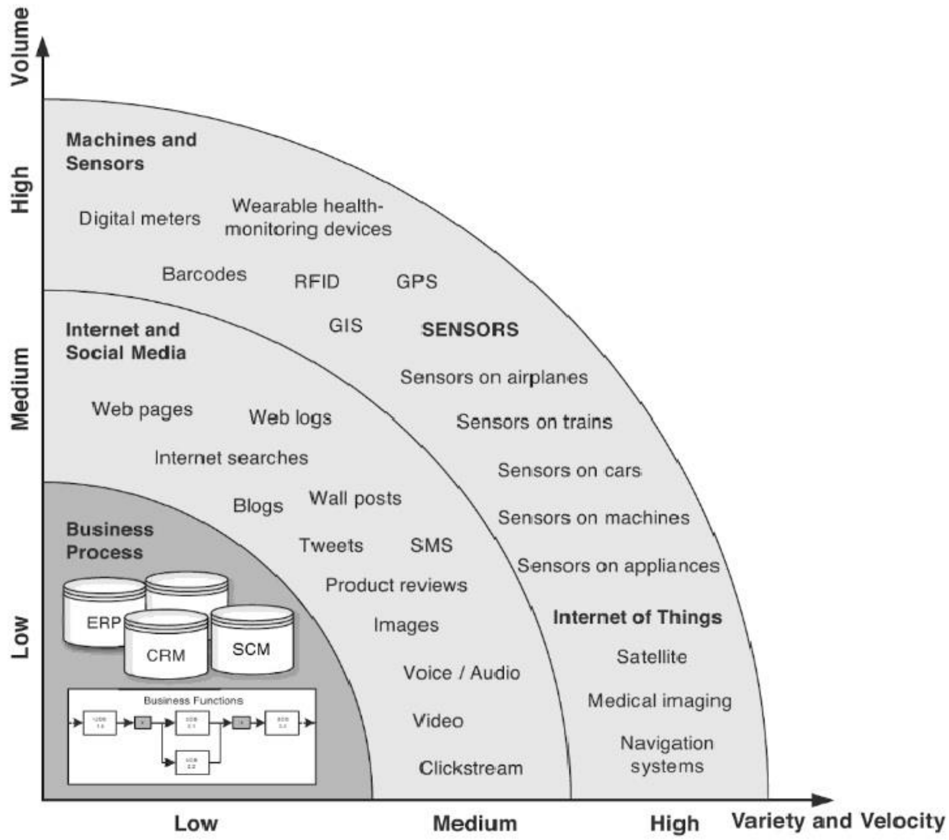

Figure 4. The wide range of sources for big data (Delen 2014: 233).

For example, in healthcare, big data can be collected in various formats from diverse sources, such as internet-based text documents, internet search indexes, sensor networks, social networks, global positioning systems (GPS), biology, genomics, biochemical experiments, medical records, scientific research, as well as genomic/biomed research (Demirkan et al. 2015: 735), and further, data in healthcare come in structured format from electronic health records (EHRs), or electronic medical records (EMRs), while semi-structured data may include instrument readings or converted paper records to electronic health records. In addition, structured and unstructured data can be streamed into healthcare systems from fitness devices, genetics and genomics, social media, and other sources. (Sakr & Elgammal 2016: 50.) According to Archenaa & Mary Anita (2015: 409) the big data sources in healthcare refer to the patient data such as doctors' notes, laboratory reports, x-ray images, national health register data, and even to RFID data of surgical instruments. In addition to patient related data, big data in healthcare settings may include also evidence-based medicine systems which doctors have traditionally been using to support decision-making (Sakr & Elgammal 2016: 56).

The above discussed characteristics and V's of big data respectively provide challenges to consider when planning how to gain value from it. The challenges and critical success factors of big data analytics are presented in the following subsection.

2.3.2. Identified challenges and critical success factors

Sivarajah et al. (2017: 263) performed a holistic review on big data and big data analytics to gain understanding in the landscape with the objective of making robust investment decisions. Based on their review, they concluded that big data challenges can be grouped into three main categories based on data lifecycle: data, process, and management challenges.

Data challenges relate to the characteristics of the data itself, e.g. data volume, variety, velocity, veracity, volatility, as well as discovery, quality, and dogmatism. Process challenges are related to a series of how techniques: how to capture data, how to integrate data, how to transform data, how to select the right model for analysis and how to provide the results. Management challenges cover for example privacy, security, governance, and ethical aspects. (Sivarajah et al. 2017: 265.) Since these challenges are presented on a general level, it can be assumed that they are universal and therefore they concern most industries utilizing big data and big data analytics, including healthcare.

The success of big data analytics in turn, depends on many critical factors (Figure 5), which according to Delen (2014: 240 – 241) need to be clarified and in place before investing in any systems or starting the analytics efforts. There should be most of all, a clear business need for performing big data analytics, aligned with the current vision and strategy of the organization. It is also important to find personnel with analytical skills, choose the right analytics tools, and ensure a strong committed sponsorship from the executive level, as without it, it would be difficult of even impossible so succeed.

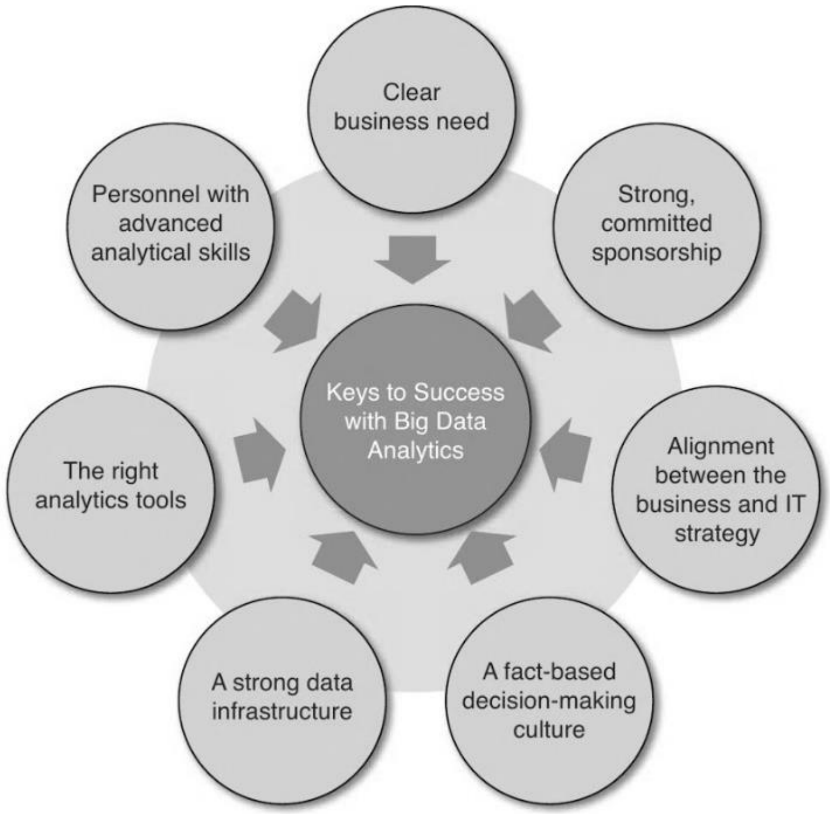

Figure 5. Critical success factors for big data analytics (Delen 2014: 240).

Generally, the purpose of various data analytics, such as business analytics is to provide insight for problem solving and decision making. Regardless they are not the same, often the terms analysis and analytics are used to refer to the same thing. To determine the term *analytics,* Delen (2014: 1) suggests that *"analytics is the art and science of discovering insight by using sophisticated mathematical models along with variety of data and expert knowledge"*, and further "*these days, analytics can be defined as simply as the discovery of meaningful patterns in data"*. Moreover, Delen (2014: 3) argues that "*analytics is a variety of methods, technologies, and associated tools for creating new knowledge/insight to solve complex problems and make better and faster decisions"*, and *"analytics is multifaceted and multidisciplinary approach to addressing complex situations*".

Hence, big data analytics and modern data mining are relatively new concepts, which also in different scope and contexts are often referred to using diverse terminology. Big data highlights the challenges related to the increased large data streams, which have been addressed with recent advancements in hardware, software, and algorithms. Data mining refers to mining corporate data to discover new and useful knowledge to improve business and its practices. Data mining plays a key role in analytics, it is "*the process of discovering new knowledge in the patterns and relationships in large data sets*". (Delen 2014: 1, 4, 14, 32 – 33.)

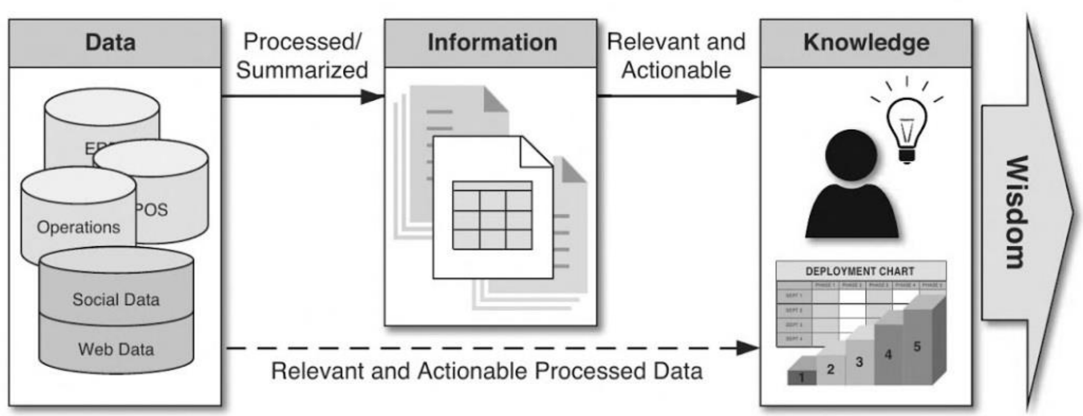

Figure 6. The continuum of data to information to knowledge (Delen 2014: 33).

Basically, data can be any data in any format, or even a combination of various data sources, i.e. big data. Data is facts, whereas information is organized and processed data, and knowledge is information which is contextual, relevant, and actionable (Figure 6). For example, according to IIHT (2013: 7) electronic health records coupled with analytical tools provide through data mining opportunity to information enabling earlier disease detection, more effective outcomes across large populations, and by that means improved population health management.

2.3.3. Taxonomy of analytics

The analytics are classified according to a simple taxonomy of analytics developed by Delen (2014: 16 – 17), into three categories, namely descriptive, predictive, and prescriptive analytics, each distinguished by the type of the data used and purpose of the analysis. According to Delen (2014: 16) most organizations begin with descriptive analytics and then move to predictive analytics and finally to prescriptive analytics which is the most advanced level of analytics. Further, he points out that moving from a lower analytics level to a higher is not clearly separable, as a business can be in the descriptive analytics level while at the same time already use partially either of the more advanced level analytics, too. The classification of analytics into descriptive, predictive, and prescriptive is also used by other scholars in their research, for example Sivarajah et al. (2017: 266), Wang, Kung, Wang & Cegielski (2017: 2 – 3) and Wang & Hajli (2017: 289).

As mentioned, *descriptive analytics* is the entry level in analytics taxonomy, and it is often referred to as *business reporting*, which provides an answer to questions such as *what happened* and *what is happening*? Delen 2014: 16). Wang & Hajli (2017: 289) agree with this as they state that descriptive analytics provides the ability to describe the data in summary form for exploratory insights and to answer to what has happened in the past. Sivarajah et al. (2017: 275) in turn state that descriptive analytics is used to identify patterns and create reports concerning past behavior, and therefore considered as backward looking and revealing only what has already happened.

According to Delen (2014: 16), organizations are mature to move to *predictive analytics* once they are ready to look beyond what happened and able to answer to question *what will happen?* Predictive analytics allow users to predict or forecast the future (Wang & Hajli 2017: 289; Delen 2014: 17) for a specific variable based on the estimation of probability, and it also enables users to develop predictive models to identify causalities, patterns, and hidden relationships. Predictive analytics provides the ability to process large volumes of both structured and unstructured data, as well as supports the data processing in real-time of near real-time. (Wang & Hajli 2017: 289.) Sivarajah et al. (2017: 276) summarize that predictive analytics aims to predict the future by analyzing current and historical data.

Prescriptive analytics uses optimization-, simulation- and heuristics-based decision-modelling techniques and tries, according to Delen (2014: 18), to answer to the question *what should I do*? Prescriptive analytics can continually re-predict and automatically improve prediction accuracy by taking in new combined structured and unstructured datasets to develop more thorough decisions (Wang & Hajli 2017: 289 – 290). Sivarajah et al. (2017: 277) explain prescriptive analytics with an example where *what if* simulators help in decision making by providing insights regarding plausible options that a business can choose to implement in order to maintain or strengthen its position in the market. A comparable situation in healthcare could be when analytics is providing insights regarding alternative interventions that a patient can choose in order to maintain or improve his or her health.

Descriptive analytics is also called *business intelligence* (BI) while predictive and prescriptive analytics are collectively called *advanced analytics*. The shift from descriptive analytics to the more sophisticated analytics is significant, since it warrants that the analytics is advanced. (Delen 2014: 16.)

Moreover, beyond this taxonomy, predictive analytics which employs complex algorithms with learning ability, may be even further classified as *machine learning* (ML), which excels at identifying latent patterns and connections that humans are too evolved to perceive (Sivarajah et al. 2017: 276; Barlow 2016: 11). Machine learning is a type of *artificial intelligence* (AI) that allows software applications to become more accurate in predicting outcomes without being explicitly programmed (TechTarget 2017). According to Gartner (2017b), "*advanced machine learning algorithms are composed of many technologies, such as deep learning, neural networks and natural-language processing used in unsupervised and supervised learning, that operate guided by lessons from existing information*". An example of artificial intelligence, is IBM's Watson, which is characterized as "smart" machine with human mind, designed to answer questions posed in natural human language. Watson is capable to analyze natural language, identify sources, find and generate hypotheses, find and score evidence, and merge and rank hypotheses. (Delen 2014: 20 – 21.) Similar artificial intelligence applications are developed continuously for various purposes, also in the field of healthcare.

2.3.4. Big data analytics in healthcare

Many businesses are operating in challenging and complex environments with an ever-increasing amount of diverse data. Therefore, to gain knowledge and get support for decision-making based on the best available evidence, businesses have begun to invest in data analytics by consciously shifting into data and evidence-driven business practices (Delen 2014: 4). In healthcare, to gain insight for better informed decisions concerning patients' health, the healthcare service providers have started to use their very large data sets for big data analytics, as its potential to improve care and save lives at lower cost have been identified (Raghupathi & Raghupathi 2014: 1, 5). Moreover, according to Delen (2014: 24), due to the fact that healthcare struggles with an imbalance between demand and supply, and increasing prices and decreasing quality, systems that has the ability to help in diagnosing and treating patients by analyzing large amounts of data, are needed.

The variety of healthcare data is large, as analytics typically aggregates data from several real-time data sources consisting of multiple data formats. Sources used in advanced data analytics can be various databases, records and systems, for example electronic health records (EHR), clinical decision support systems, as well as web and social media data (e.g. clickstream and interaction from Facebook, blogs, health plan websites, smartphone apps), machine to machine data (readings from remote sensors, meters and other vital sign devices), biometric data (e.g. finger prints, genetics, x-ray and other medical images, blood pressure, pulse and pulse-oximetry readings), and human generated data (e.g. email, paper documents). Data types can vary from structured data, e.g. traditional electronic health care records, and semi-structured data, e.g. the logs of health monitoring devices, to non-structured data, such as notes or clinical images. The analytics tools and architecture for structured and unstructured big data differ from traditional data management and business intelligence tools where the data is assumed to be certain, clean, and precise. (Raghupathi & Raghupathi 2014: 4 – 5; Wang et al. 2016: 2 – 3.)

Handling data from various sources is challenging because the characteristics of the collected data might vary considerably (Wang et al. 2016: 2). For example, as big data is often unstructured, messy, and dirty it means that the organizations need to have ability and capability to handle the fast arriving data so that it can be converted into actionable insight (Delen 2014: 8). Regardless which data sources or formats are used, the veracity of the data needs to be validated before analyzing it, meaning that it must be ensured that the analyzed data is of high quality, truthful, and accurate by making sure that the diagnoses, interventions, and outcomes are captured correctly in the data sources (Raghupathi & Raghupathi 2014: 4).

Obermeyer & Lee (2017: 1211) are concerned regarding the data analyzed with highly accurate algorithms and bring out some criticism for the veracity of the data. They warn that ignoring clinical thinking and relying solely on analytics is dangerous, as the analyzed data is always based on human decisions and human mistakes, which can lead to failures. Therefore, it is important to consider analytics as thinking partners, not replacements for doctors, who need to be trained to utilize analytics to master the complexity of modern medicine and patients with more coexisting illnesses and medications (Obermeyer & Lee 2017: 1209, 1211).

According to Delen (2014: 9), some criticism has been brought out also toward data and data analytics, most commonly regarding security and privacy issues due to the risk of breaches of sensitive information and leaking or misuse of personal data. Moreover, Gumbus & Grodzinzky (2016: 118) raise their concerns of the rise of computational power and cheaper and faster devices to capture, collect, store and process data which can lead to "datafication" of society and cause discriminatory practices as its side effects, e.g. in a situation where analytics lead to harmful or unfair outcomes for individuals or populations.

However, despite of the hurdles in the way, big data analytics is a powerful tool, as it enables organizations to gain new insights into organizational knowledge, which can be used in decision making and action taking. Using this kind of advanced analytics is not only a matter of increased productivity or efficiency, but also of intangible values such as increased flexibility and quality improvement. (Wang, et al. 2017: 3 – 4.)

2.4. Big data analytics-enabled transformation model

To find out the business value and potential benefits of big data analytics for the healthcare industry, Wang & Hajli (2017: 287) developed a big data analytics-enabled business value model using the resource-based theory and capability building view. The theory models the big data analytics components, capabilities, and benefit dimensions, but does not build a view on value co-creation practices related to healthcare service delivery. Another theory addressing the same subject is the big data analytics-enabled transformation (BDET) model (Figure 7) developed by Wang et al. (2017: 2) who supplement the model with a practice-based view from strategic management to explain how big data analytics can enable organizations to develop inimitable practices, which in turn are intended to create business value.

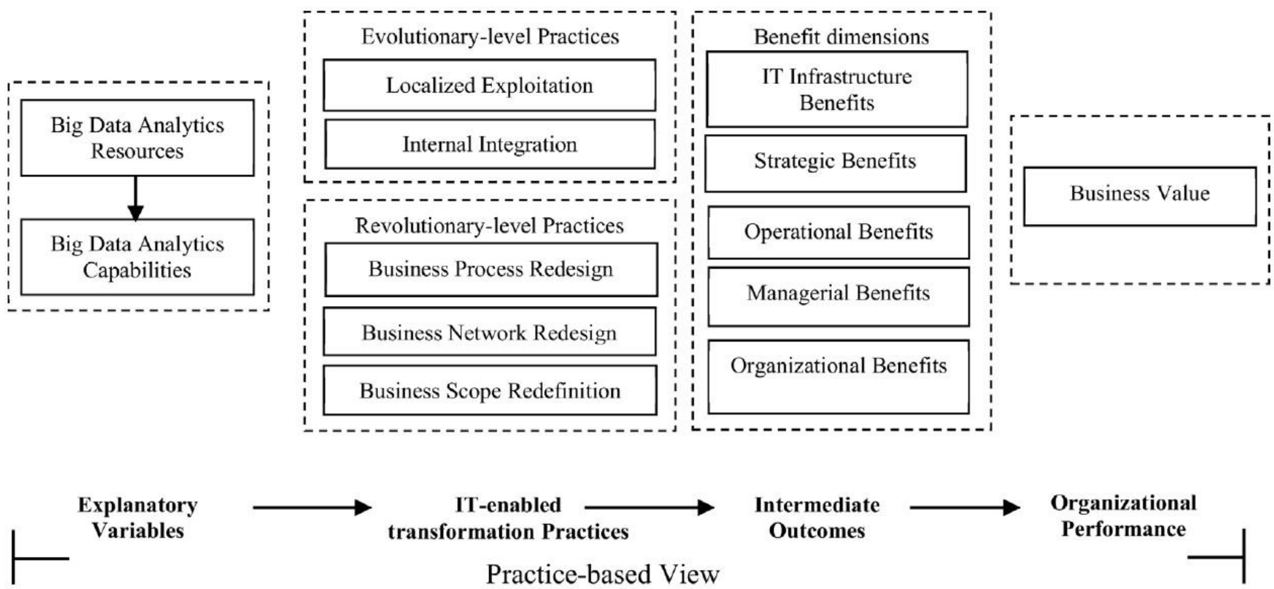

Figure 7. Big data analytics-enabled transformation model (Wang et al. 2017: 2).

The model aims to explain how big data analytics capabilities can create potential benefits and business value for a healthcare organization (Wang et al. (2017: 2). The linear progress path of the model follows a practice-based view developed by Bromiley & Rau (2014: 1252 – 1253), who argue that practices are important entities in and of themselves, rather than simply indicators for some underlying construct.

Hence, both theories and developed models seek to discover the potential benefits and business value of big data analytics in healthcare context, but as the big data analytics-enabled transformation model by Wang et al. (2017: 2), also includes the practice-based view, it is more suitable for this study because these practices, even though intended to be inimitable, can be viewed from the value co-creation perspective as well. The BDET model is explained in more detail in the following paragraphs.

2.4.1. Components of BDET model

Explanatory variables

The explanatory variables of this model refer to the *big data analytics capabilities* generated from *big data analytics resources*, that are big data analytics architectural components. The resources that together build the analytic capabilities consist among others of the data itself, managerial and technical skills, and data-driven culture of the organization. Further, the tools and functionalities of big data analytics are identified to consist of three architectural components, namely data aggregation, data analysis and data interpretation which allow users to transform data into evidence-based decisions and informed actions. (Wang et al. 2017: 2.)

Data aggregation component aims to collect heterogeneous data from multiple sources, e.g. data warehouses and databases, and transform it into specific data formats which can be read and analyzed. In this phase, according to Wang & Hajli (2017: 289), after data is collected and extracted from various sources, *data analysis* component explains how all kinds of data is processed (e.g. data mining or natural language processing) and how analyses are performed so that they support evidence-based decision making and meaningful practices in healthcare organizations. *Data interpretation* component generates general clinical summaries such as historical reporting, statistical analyses, time series comparisons, provides data visualizations and real-time reporting such as alerts, proactive notifications, and operational key performance indicators (KPIs), as well as meaningful business insights derived from the analytics components. (Wang et al. 2017: 2 – 3, 6.)

To evaluate the *analytics capabilities*, the model breaks them down into *traceability* which refers e.g. to the capability of tracking medical events and searches in clinical databases; *analytical capability* which refers to the nature of the analysis, e.g. understanding the past and current state of variables, causes of occurred medical events and support of real-time processing; *decision support capability* which refers to real-time or near real-time clinical summaries presented in visual dashboards; and *predictive capability* which refers to the capability to examine undetected correlations, patterns and trends between specific variables, compare current and historical data, predict future trends, and provide actionable insights or recommendations in readable format (Wang et al. 2017: 6 – 7). Wang & Hajli (2017:290) in turn, base their definition in information lifecycle management, and define big data analytics capability in the healthcare context as "*the ability to acquire, store, process and analyze large amounts of health data in various forms, and deliver meaningful information to users, which allows them to discover business values and insights in a timely fashion*".

IT-enabled transformation practices

The BDET model explores seven different IT-enabled practices listed in Table 3. The practices are classified into localized exploitation, internal integration, business process redesign, business network redesign, and business scope redefinition. The two first classification levels are evolutionary transformation level practices and the last three are considered to be revolutionary transformation level practices. (Wang et al. 2017: 2 – 3, 7.)

Table 3. IT-enabled transformation practices with examples (Wang et al. 2017: 7).

Classification of IT-enabled transformation practice	**Examples**
Localized exploitation: 1. Meaningful use of EHR (electronic health record) practice	Generate lists of patients by specific conditions to use for reduction of disparities, research or outreach Improve care coordination among healthcare units through interoperable EHR systems
Localized exploitation: 2. Evidence-based medicine practice	Explore the fact from medical events or patient treatments to improve specific outcome Build holistic view of evidence by insights from literature-based data and research studies
Internal integration: 3. Multidisciplinary practice	Provide joint decisions regarding treatments to patients from a multidisciplinary team

Business process redesign: 4. Clinical resource integration practice	Allocate resources to serve each healthcare unit Create centralized information support for clinical operation
Business network redesign: 5. Network collaboration practice	Build common understanding of healthcare service between care providers and other stakeholders
Business network redesign: 6. Network knowledge creation practice	Allow all stakeholders to share information on the platforms Discover new knowledge by enabling stakeholders to collaboratively map ideas
Business scope redefinition: 7. Personalized care practice	Create personalized disease risk profile and disease and wellness management plan for each patient

The IT-enabled transformation practices presented in the BDET model can be linked to the co-creation typology (Table 1) introduced by Frow et al. (2016: 31 – 33). For example, personalized care practice can be linked with the practices that shape an actor's mental model and practices that shape existing value propositions and inspire new ones (CP3 and CP5). Also, clinical resource integration practices can be linked with practices that shape an actor's mental model (CP3), as they are affected by how the personalized care practices are arranged. In addition, meaningful use of EHR and evidence-based medicine practices can be linked with the practices that impact access to resources within an ecosystem (CP6), e.g. in form of shared knowledge resources. Multidisciplinary practices, network collaboration practices and network knowledge creation practices can be linked to the practices that forge new relationships, generating interactive and/or experiential opportunities (CP7), e.g. when collaboration between various specialties in hospital or cross-boundary cooperation between health and social sectors are developed.

Intermediate outcomes

Wang et al. (2017: 2 – 3) treat intermediate outcomes in the BDET model as benefits. To conceptualize the potential benefits, they apply a multidimensional information system (IS) benefit framework developed by Shang & Sheddon (2002: 277 – 280) who have identified five benefit dimensions in their research. Also, Wang & Hajli (2017: 293) use this benefit framework and provide some examples on practical benefits. The benefit dimensions and a summary of selected examples are listed in Table 4.

Table 4. The benefit dimensions with examples of subdimensions (Shang & Sheddon 2002: 277; Wang et al. 2017: 3; Wang & Hajli 2017: 290, 293).

Benefit dimensions	Description	Examples of subdimensions
Operational benefits	The benefits obtained from the improvement of operational activities	Productivity improvement Quality improvement Customer service improvement Cycle time reduction Cost reduction Immediate access to clinical data for analysis Enable proactive treatment before the condition worsens
Managerial benefits	Benefits obtained from business management activities, e.g. allocation and controlling of resources, monitoring of operations, and supporting business strategic decisions	Better resource management Insights and sound information for decision-making and planning Performance improvement
Strategic benefits	Benefits obtained from strategic activities involving long-range planning regarding high-level decisions	Support for business growth Support for business alliances Building business innovations Achieving business competitive advantages: cost leadership, differentiation, and focus Comprehensive view of treatment delivery for meeting future needs
IT infrastructure benefits	Sharable and reusable IT resources providing foundation for present and future business applications	Increased IT infrastructure capability Reduce of system redundancy Transfer data quickly among healthcare IT systems Simplified IT management IT cost reduction

Organizational benefits	Benefits related to organization’s focus, cohesion, learning, and execution of chosen strategies	Seamless and coordinated patient experience delivery Changing work patterns Facilitating organizational learning Cross-functional communication and collaboration Building common vision

Organizational performance

In the BDET model, organizational performance refers to business value (Wang et al. 2017: 2). Both Wang et al. (2017: 3) and Wang & Hajli (2017: 290) argue that using Shang & Sheddon’s framework helps to understand the potential benefits of big data analytics and enhance the understanding of the business value of big data. It also acts as a tool for managers to assess the benefits of their firm’s information systems, which means that the model could also be used as a general model and guideline for assessment and classification of benefits from IT architecture.

2.4.2. Big data-enabled transformation and value co-creations practices

Since one of the objectives of this study is to indicate the possible transformation of selected value co-creation practices and evaluate their impacts to the healthcare ecosystem, the IT-enabled transformation practices of the BDET model are viewed as value co-creation practices (cf. Frow et al. 2016: 31 – 33). Additionally, this enables the disclosure of the nature of the indicated transformation of the value co-creation practices, which can be considered as evolutionary or revolutionary. Another objective of this study is to discover the potential benefits and value from several stakeholder groups’ viewpoints. Therefore, in addition to the business value perspective, the model is extended with viewpoints of value for individual patients and population health. The individual patient’s perspective is important to understand in order to be able to develop the personalized patient centric care and motivate the patients to participate and acquire a more active role in their own care planning and shared decision-making. Regarding the population health perspective, it is essential to understand the generated value because it provides insights on how healthcare services should be targeted to close the indicated care gaps, which further supports the desired shift into value-based healthcare. Hence, the extended BDET model studies the value of big data analytics for three stakeholders. In case the findings show clear paths-to-value, they can also be illustrated with this model.

Regarding the explanatory variables, big data analytics resources are studied through breakdown into data aggregation, data analysis, and data interpretation, and the capabilities in turn through breakdown into traceability, analytical capability, decision support capability, and predictive capability (Wang et al. 2017: 6, 10).

To conclude, the original BDET model is extended as explained (Figure 8), and used for studying and analyzing the case, i.e. the Health Benefit Analysis tool, developed in a project funded and run by Sitra. The case, and the development project are introduced in more detail in chapters 3 and 4.

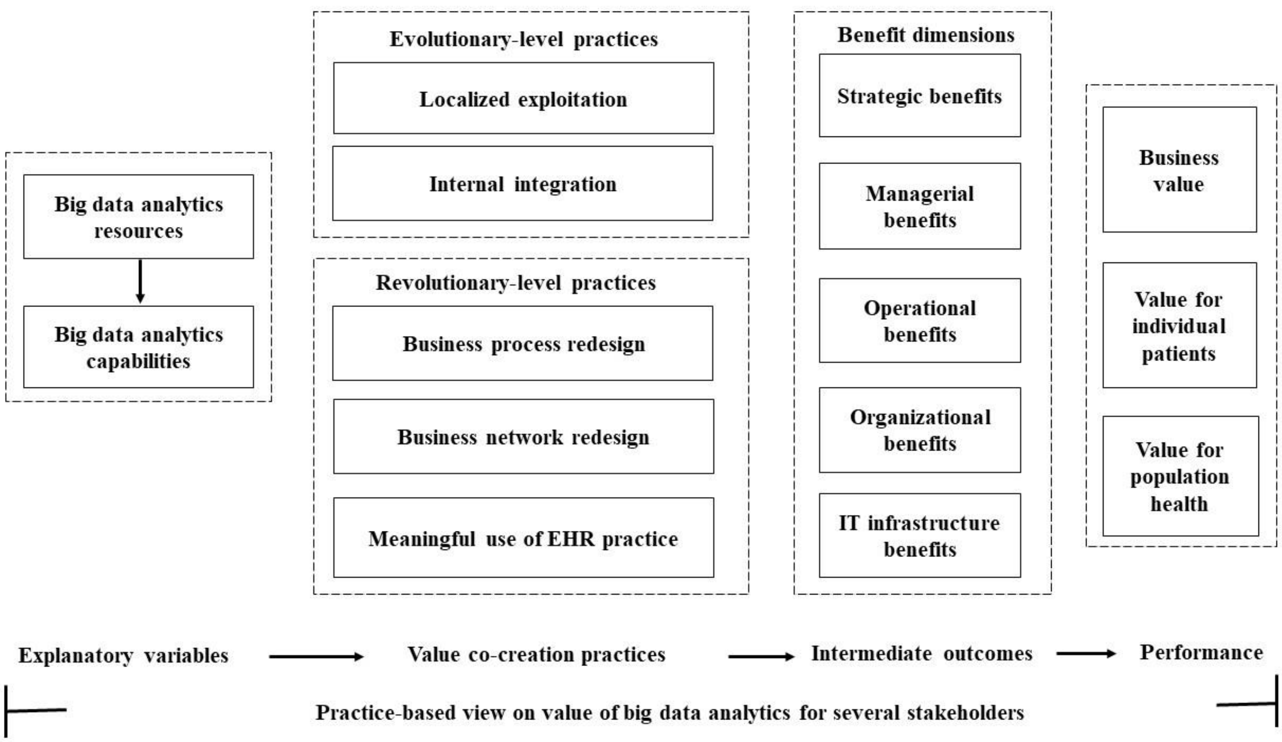

Figure 8. The extended big data analytics-enabled transformation model (adapted from Wang et al. 2017: 2).

The big data analytics-enabled transformation model is aligned with the research questions and applied for studying and analyzing transformation practices as value co-creation practices and evaluating the performance with business value extended with value for individual patients and population health.

3. METHODOLOGY

In this chapter, the choices regarding the methodology of this study are presented and justified. First, the research type is indicated, then the selected strategy and approach of the study are presented, continued with research design through selected research method and decisions regarding empirical data collection methods and analyzing process. In the end of this chapter, the validity and reliability of the study are discussed.

The purpose and objective of this study is to find out how using advanced analytics of big data can create potential benefits and value for selected stakeholders, and how it affects the value co-creation practices in the selected service ecosystem. This objective explores a situation explaining the relationship between variables, that is the relationship between analytical capabilities of advanced analytics and performance, i.e. value created for the stakeholders. Also, the relationship between current and transformed value co-creation practices is addressed in the study. By that means the type of this study can be considered *explanatory*. However, as the study also provides insights into a relatively new field, and since there is an indicated research gap of potential business value through big data analytics in healthcare context, the type of study can also be regarded as *exploratory*. (Yin 2009: 9.)

3.1. Research method

In business research, case studies are popular research methods, suitable especially for investigating contemporary phenomena within real-life contexts. In a practical business-related case study, the researcher can study even complex business issues by depicting the specific research problem, collecting, and analyzing empirical data, and in the results, suggest or recommend how to overcome the problem in this specific business context. (Eriksson & Kovalainen 2008: 116, 118.) Moreover, Maylor & Blackmon state that when the study is limited and exploratory in nature, a case study is useful and the most suitable methodological choice (2005: 243).

As this study examines a specific complex business issue using a specific Health Benefit Analysis (HBA) tool as a unit of analysis, the selected *research strategy* is a *single case study*. At the time of this study, the development of the HBA tool was at the pilot stage. The

HBA tool is a suitable case for this study in terms of its analytical features and value promise, as well as due to the availability of the subject matter experts for interviews. In addition, according to Yin (2009: 13), a case study has distinct advantages when a how question is being asked about a contemporary set of events over which the researcher has little or no control.

The *research approach* of this study is *deductive* as the research proceeds from theory to empirical testing. In deduction, also the literature leads to hypothesis or research question. The process of deduction is linear and follows the logic of proceeding from theory to empirical study. (Eriksson & Kovalainen 2008: 21 – 22; Maylor & Blackmon 2005: 150.) In this study, the empirical data collected in semi-structured interviews and from other sources are evaluated using the selected theoretical model acting as starting point for what is already known about the phenomenon. However, the theoretical model is slightly modified before it is used for empirical testing. The reason for modification is the interest to examine the performance from extended viewpoints and to study the practices not only from information technology but also from value co-creation perspective. For knowledge production in business research an adequate approach is to use the *qualitative research methodology* (Eriksson & Kovalainen 2008: 5). As this study aims at explanatory and holistic understanding of the studied issue, the qualitative approach is the methodological choice in this study. The choices regarding the research design are explained in the following subsections.

Research design refers to the logical sequence that connects the empirical data to the initial research, i.e. the logic that links the data to be collected and the conclusions to be drawn to the initial questions of the study (Yin 2009: 24, 26). As stated above, the framework for conducting this study is a qualitative single case study. In case study, a phenomenon in a selected unit of analysis is explored in detail using a variety of methods, usually over a period of time. In this study, the single case study research method is used since the case is a unique tool, and because the study is evaluating the empirical data to learn whether the propositions of the theoretical model can be identified (Yin 2009: 47). The time horizon of this study is cross-sectional as the data was collected at a certain point of time, namely when the case tool was about to enter the pilot phase, where it is implemented for test use in selected health centers.

3.2. Sampling and case selection process

The criteria for selecting the case for this study were 1) the case presents a real-world implementation of advanced analytics of healthcare big data and 2) its value promise includes generating benefits and value for individual patients, populations, and healthcare service providers. The boundaries of the selected case are limited to a single tool (Maylor & Blackmon 2005: 244), that fulfills the mentioned criteria, and contributes to answering to the research questions.

The selected case, the HBA tool, was found via the Finnish Innovation Fund Sitra, which is the sponsor of the HBA tool development project. The HBA tool is developed in Finland and it uses data from various sources, including electronic health records of Finnish citizens. The value promise includes reduced care gaps and equal opportunities to healthcare in timely and cost-effective manner, which also meets the set selection criteria.

The HBA tool development project has multiple goals where the main objective is to develop an analysis tool, which can analyze health data combined from various sources, and indicate patients suffering from potential care gaps, or cases of overtreatment. The aim is to develop a personal and systematic care need assessment which ensures access to treatment early enough for everyone that will benefit from the particular treatment, as well as reduce health inequalities among population (cf. Airoldi et al 2014: 965, 970). The purpose of the HBA tool is also to improve the cost-efficiency of healthcare services in Finland and facilitate a broader analysis of the overall status of disease treatment, such as having to do with medication, and, in turn, develop healthcare services to better meet the needs of various patient groups. Moreover, the developers aim to commercialize the HBA tool, targeted to both domestic and international markets. (Sitra 2016.)

To find out how the expected benefits and values are achieved, and how using advanced analytics affects the related value co-creation practices, a sample of organizations and people were used. In order to build a comprehensive view of the case, an interviewee (Maylor & Blackmon 2005: 63) was selected from each development project participant organization, as well as several experts representing stakeholder organizations conducting parallel development closely related to the HBA tool. This sampling method represents nonprobability or purposive *deliberate sampling*. More specifically, the sampling method in this study is *convenience sampling* where the sample is selected based on the ease of access. Also, the *judgement sampling* is used as the researcher's judgement is used for selecting the interviewees in the case. (Kothari 2004: 15.)

3.3. Data collection and analysis

In case studies, the empirical data can be retrieved from multiple sources. In business-research, the primary source of empirical data are in-depth interviews. In addition, other sources can be used to complement the data collected in interviews. Other sources are for example documents such as minutes of meetings, letters, reports, statistics, archival records, articles, as well as digital materials such as web pages, e-mails, or chat conversations. (Eriksson & Kovalainen 2008: 125 – 126.)

The interviews as empirical data collection method can be structured or unstructured. According to Maylor & Blackmon (2005: 230 – 231), highly structured interviews can be characterized with closed questions where the interviewee need to answer all questions in the questionnaire in a structured manner, while in unstructured interviews the interviewees are asked open questions to discuss the topic on a general level and where the emergent concepts are included in the discussion during the interview.

In a semi-structured interview, the discussion topics, and themes, as well as related questions are prepared before the interview takes place. In the interview, the interviewer is leading the discussion by asking the planned questions but is not limited to the questionnaire only. Instead, the interviewer is prepared to ask additional questions if the interviewee brings up a new relevant issue related to the research question. The semi-structured interviews are quite conversational and unformal, which requires paying attention so that all planned topics are covered in the interview. (Eriksson & Kovalainen 2008: 82.) According to Yin (2009: 69), the interviewer should have a firm grasp to the issues being investigated and be a good listener who is able to ask good questions and interpret the answers. To be able to plan relevant questions for the interviewees in this study, the characteristics of the planned Health Benefit Analysis tool was investigated in advance using the provided materials. Also, the concepts of individual and population health management, health benefit analysis, care gap analysis, value-based healthcare, and big data analytics in healthcare context were studied. The interview questions were planned so that they help to find answers to the research questions. Also, the planned theoretical framework was considered when planning the interview questions, e.g. how big data analytics may affect the co-creation practices in the healthcare ecosystem and what the possible benefits for the defined stakeholders could be.

Information gathering in discussions and meetings

In this study, data has been retrieved first by preliminary discussions with the project sponsor and main developer as indicated in Table 5, and by gathering information from the provided project documentation as well as from other project specific source materials such as web pages. (Yin 2009: 101 – 103.)

Table 5. Information gathering through preliminary discussions.

Discussion	Organization	Date	Recorded / Notes taken
Project Director, Human-Driven Health / Senior Lead	The Finnish Innovation Fund Sitra	23.05.2017 24.05.2017 01.06.2017 22.06.2017 04.09.2017	Notes taken
Medical Doctor, Ph.D. / Editor-in-Chief / Original idea and main development of the HBA tool	Duodecim Medical Publications Ltd.	29.05.2017	Notes taken

Conducting the interviews

After the preliminary data was collected, a semi-structured interview was planned, and discussion themes and main questions formulated (Appendix 3). The questions include general orientation questions regarding the reasons for the development and interviewees role in the project, as well as detailed questions following the patterns of the selected theoretical model of the study. In addition, some questions related to the possible challenges related case project or developed tool were included. (Yin 2009: 87, 106 – 109.)

The interviews were conducted with eight interviewees representing the different organizations involved in the case project. Most of the questions were answered with long replies, but some of the questions were more challenging to answer and they had to be clarified, e.g. regarding the potential benefits, the interviewer clarified with statements which the interviewee accepted or rejected. The interviews were carried out online with Skype for Business and recorded. The recordings were transcribed into text format for analysis purposes. The interviewees are representatives of the Health Benefit Analysis tool development project parties and related experts. The time and duration of each interview is summarized in Table 6.

Table 6. List of interviewees, time schedule and duration of interviews.

Interviewee / Role in the project	Organization	Date of interview	Duration	Recorded / notes taken
Senior Lead / Project Director	The Finnish Innovation Fund Sitra / sponsor	22.09.2017	65 min.	Recorded
Project Manager in the piloting health centers	City of Helsinki / Selected health centers	26.09.2017	48 min.	Recorded
Medical Doctor, Ph. D. / Service Operator for Well-being / Senior Advisor	The Finnish Innovation Fund Sitra	26.09.2017	41 min.	Recorded
Medical Doctor, Ph.D. / Editor-in-Chief / Original idea and main development of the HBA tool	Duodecim Medical Publications Ltd. and Health and Social Security Enterprise Saarikka	27.09.2017	64 min.	Recorded
Research Principal Lecturer / Welfare Technology Expert	Satakunta University of Applied Sciences	27.09.2017	50 min.	Recorded

Professor / Development Advisor	Tampere University of Technology	28.08.2017	49 min.	Recorded
Project Manager in the piloting health center	Health and Social Security Enterprise Saarikka	29.09.2017	62 min.	Recorded
Project Director / Self-care and Self-help Expert	City of Espoo / ODA Project (Self Care and Digital Value Services)	04.10.2017	50 min.	Recorded

Data analysis

In qualitative research it is common that the distinction between data collection and data analysis is not clear, rather they are intertwined and closely related to each other. Likewise, in this study, ideas for classification and organizing interview data began to emerge already during the data collection and interview phases. (Eriksson & Kovalainen 2008: 299 – 300.)

To analyze the collected empirical data, for this study the most suitable strategy is to rely on theoretical propositions as it helps to organize and focus on relevant data (Yin 2009: 130). Moreover, since the patterns and concepts of the theoretical model were already used as a starting point for designing the research questions, it is naturally clear that this will follow throughout the analysis process as well.

In practice, the transcribed empirical data is first classified and organized anonymously, according to the same themes as used in the research questions which again are based on the BDET model. The answers of all interviewees are compiled and summarized thematically (Eriksson & Kovalainen 2008: 128), which after the data is analyzed by building an explanation about each theme. The themes used in the compilation are, in addition to the project scope and participants description, the big data analytic components and capabilities describing and explaining the HBA tool resources and characteristics of analytical level. Moreover, the value co-creation practice break-down and benefit dimensions with respective examples are used as themes in accordance with the BDET model. Classification of the empirical data according to these themes, enables the explanation of the phenomena in narrative form. (Yin 2009: 141.) The analysis and explanations are written in the stated order and respectively supported with anonymous quotations from the interviews. Pattern matching, which according to Yin (2009: 136), in explanatory studies can indicate the dependencies between variables, is applied when indicating the paths-to-value chains, i.e. what kind of analytic capability leads through a specific value co-creation practice to a certain benefit that creates value. The paths-to-value chains are drafted last to summarize the analysis and provide answers to the research questions.

3.4. Validity and reliability

Validity of a case study can be tested with four tactics that are construct validity, internal validity, external validity, and reliability. *Construct validity* is ensured in this study with using multiple sources of evidence, i.e. several interviewees in the data collection phase and case project related documentation, and by having key informants to review the draft case study report to check that the context related information and other details regarding the case specific information is understood and reported factually correctly. (Yin 2009: 41 – 42.) *Internal validity* is mainly a concern for explanatory case studies where the researcher is trying to explain how and why an event led to another. Another concern regarding this tactic is the problem of making the right conclusions based on the evidence and reasoning. In this study the internal validity is aimed to be verified by using pattern matching and explanation building. (Yin 2009: 42 – 43.) *External validity* deals with the problem of knowing whether the case study's findings are generalizable. Typically, single case studies offer poor basis for generalizations (Yin 2009: 43) for the entire population. As this study is a qualitative single case study and unique in nature, it only aims at theoretical generalization.

Reliability of a study means that the study procedures are documented to the extent, that if another researcher later conducts the same case study, the findings and conclusion should arrive at the same (Yin 2009: 45). The semi-structured interview questions, empirical data, references, and the applied theoretical model are well-documented and by that means the repeatability and reliability of this study are ensured. Reliability and transparency are also achieved by linking the analysis results with references to theory.

4. EMPIRICAL FINDINGS

In this chapter, the studied case and its development project are presented. Also, the project participant organizations' roles, and objectives for participating in the project, are introduced. In addition, some other organizations that carry out development closely related to the case project are also presented. Their representatives have been interviewed in this study in order to gain better understanding on the studied topic and being able to find more versatile answers to the research questions. Thereafter, the empirical findings are presented according to the selected theoretical model and discussed so that first, the basic features of the Health Benefit Analysis (HBA) tool, as well as its resources and capabilities, are described, followed by presenting its changing effects on value co-creations practices. Moreover, the impact of introducing advanced analytics to the healthcare ecosystem, and its effects on value co-creation actors are indicated and discussed. Finally, the discovered potential benefits and performed value for the selected stakeholders are presented.

4.1. Case: The Health Benefit Analysis tool

The case, the HBA tool, is developed and implemented to conduct health benefit analyses as described in subsection 2.1.1. and presented in Figure 9. The purpose of the HBA tool is to analyze combined sources of patient data to provide a list of net impacts of different interventions. For an individual patient, a health impact can be considered a benefit or a harm. On population level, the HBA tool helps the healthcare service providers to allocate resources for medical services and interventions by listing how many people would benefit from each intervention complemented by numbers that indicate the average health impact of each intervention.

The HBA tool development project

The HBA tool development project is introduced based on pre-discussions with the development project director and the main developer of the HBA tool. Also, information provided on Sitra's (2016) website, and other related materials are used. The role of each participant organization and the relation of the additional organizations to the HBA tool and the development project, are also complemented with information provided by the respective interviewees.

The development project's official name is "Health Benefit Analysis, From Quality Data to Effectiveness project". The Finnish Innovation Fund, Sitra, is the sponsor of the project. The project was initiated in September 2016 and it will run until the end of 2018. Sitra's partners in the project are Duodecim Medical Publications Ltd., City of Helsinki, and the health and social security enterprise Saarikka, which consists of the municipalities of Kannonkoski, Karstula, Kivijärvi and Kyyjärvi and the City of Saarijärvi. (Sitra 2016.) Other organizations having related projects in the subject matter area are Satakunta University of Applied Sciences (SAMK) and Tampere University of Technology (TUT), which are developing an educational program for health analysts, professional experts in conducting and interpreting the health analytics and acting as advisors in healthcare and social welfare services, and City of Espoo, which is running the ODA project developing self-care and digital value services for citizens. These organizations are participating or related to the development of HBA tool as follows:

Sitra, the project owner, is funding the development of the HBA algorithm, program code, and the pilot testing of the tool. Among the reasons for supporting the development of the HBA tool is its value promise according to which the HBA tool provides support in decision-making for the healthcare professionals, as well as offers the service users new ways to assess their health status. (Sitra 2016.) Also, in near future, according to the ongoing healthcare reform in Finland, the healthcare services are organized by counties which would benefit of using the HBA tool when planning and implementing the healthcare services on upper levels of the healthcare ecosystem. Moreover, it can be stated that Finland is a propitious country to develop this kind of tool, because several useful data sources already exist, which, in future, combined with the data collected from the personal wellness equipment of individuals constitute the big data repository for the analyzing purposes. In addition, this digital medical intelligence combined with the knowledge that the structures of Finnish society enjoy its citizens' trust are the ingredients for developing a successful product, even for international export. (Sitra 2016.) In practice, Sitra is also having an advisory role in the project, as it is supporting the development work with its own expertise regarding the digitization of social welfare and healthcare services.

Duodecim Medical Publications Ltd., a company owned by The Finnish Medical Society Duodecim, is the main developer of the HBA tool. The society has over hundred years, since its establishment in 1881, been developing the professional skills and clinical practice of doctors through continuous education, publications, and grants. Duodecim Medical Publications Ltd. publishes content intended for healthcare professionals as study materials and to support their daily work, e.g. evidence-based medicine guidelines, evidence-based medicine electronic decision support system (EBMeDS[3]), and Current care guidelines[4]. (Duodecim 2017.) Moreover, since Duodecim has over the years produced medical information for healthcare professionals and citizens, first in form of magazines and books, and then via electronic information portals, it is now broadening its services into new integrated information systems, such as the HBA tool which, in practice, is built on the EBMeDS.

The City of Helsinki, is participating in the HBA tool development project as a pilot user and a contributor of the development of desired functionality of the tool. The tool is piloted in two health centers in Helsinki, which in this study represent healthcare service providers (Figure 1). In these health centers, the electronic health records are used for the analysis purposes, and the health benefit analyses are conducted with selected individual patients when they visit the health center at the doctor's or other health professional's reception. The City of Helsinki is participating in this project since it is aiming at reducing the health and wellbeing inequalities among citizens, as well as improving the productivity, effectiveness, and accessibility of healthcare services. The HBA tool is useful for that purpose.

The Health and Social Security Enterprise Saarikka, is also participating in the HBA tool development project as a pilot user and contributor to the development of the tool. In this study, also Saarikka represents a healthcare service provider (Figure 1). In Saarikka, the tool is piloted more widely, as the health benefit analyses are planned to be carried out as a virtual health assessment for the whole population of Saarikka. By conducting this kind of virtual health assessment, it is possible to find the patients' hidden needs for interventions. The intention is to invite the discovered high-risk patients to visit the healthcare professionals according to their individual needs. In this project, Saarikka is also aiming at developing its

[3]EBMeDS, Computerized clinical decision support rules:
https://www.duodecim.fi/english/products/ebmeds/
[4]Current care guidelines: https://www.duodecim.fi/english/products/current-care-guidelines/

practices regarding the recording of patient records. In addition, Saarikka expects that the results of this project will help with planning the future development of healthcare services.

The Satakunta University of Applied Sciences (SAMK) and *the Tampere University of Technology (TUT)*, are currently developing and carrying out the first educational program intended to train health analysts. This is a new profession in the field of healthcare and wellbeing. The trained health analyst professionals are planned to use the HBA and other analytical tools, interpret, explain, and discuss the results and possible interventions with patients. In practice, the training program is conducted in cooperation with local county healthcare service organizer and service providers such as regional and central hospitals.

The ODA, Self Care and Digital Value Services project[5] is one of the key projects in the field of health and wellbeing set by the Finnish Government Programme[6]. The project is led by the City of Espoo but implemented simultaneously in several Finnish hospital districts and cities, e.g. in Helsinki, Tampere, Lahti, Turku, Oulu and Hämeenlinna. The ODA is planned to be in use throughout Finland in 2018. The plan is, that the development carried out in the ODA project later enables the integration of the patients' self-measured health data in the data sources of the HBA tool, which will enrich further the analytics results generated by the tool (cf. Appendix 2: 15).

In the following subsections, all required big data components and analytical capabilities, value co-creation practices, potential benefits and created value are studied and analyzed using the applied BDET model (Figure 8) introduced in subsection 2.4.2. as a framework.

4.2. Health Benefit Analysis tool explanatory variables

To successfully achieve the potential benefits and create value with the HBA tool, a set of explanatory variables are needed. As a starting point, a qualified patient data repository and specific rules for filtering the patient data are required. The HBA tool is planned to collect

[5] About ODA project, in Finnish: https://www.kuntaliitto.fi/sites/default/files/media/file/ODA-esite.pdf
[6] Implementation of the Government Programme: http://valtioneuvosto.fi/en/implementation-of-the-government-programme

and combine data from several different sources, and with an algorithm developed for the purpose analyze and provide support for healthcare professionals in decision-making, e.g. which interventions should be made, and in which order the interventions should be implemented. In practice, the HBA tool is embedded as an additional feature in the EHR system interface. Health centers in Helsinki and Saarikka currently use the Pegasos EHR system, which contains all patient's data mainly in structured format, provided that the health professionals using the system have managed to enter the data in the system correctly and according to the standardized and pre-defined structure, which also enables more feasible individual care planning (cf. Health Level Seven International: 2013). Having correct patient data in the correct format in the EHR system is the pre-requisite for successful and valid results of the analytics.

4.2.1. Big data analytics components

The big data analytics resources of the HBA tool consist of several architectural components, that are the patient data repository, for example the Pegasos EHR and personal health records retrieved from My Kanta[7] as planned in the ODA project. In future, it is possible that data repositories include biobanks and genome databases, too. Evidence and guidelines are based on the EBMeDS rule set, based e.g. on systematic reviews provided among others by Cochrane[8]. Currently, the patient data used for analysis is in a structured and coded format. The HBA tool does not process any unstructured or semi-structured data at this point. As the volume of the data is already large and growing, and the velocity of generating new data in the system is increasing, as well as the variety of the data is becoming more versatile, it can be claimed that the definition of big data is fulfilled (cf. Berman 2014: xx).

The analysis itself is conducted by EBMeDS' rules engine and risk calculators, which are algorithms that for example, examine the data and analyses whether a person belongs to a certain patient group, does the patient have a certain disease, and does he or she have a risk, which indicate a need for medication, picks up these patients from the database and suggests intervening with specific medication. The HBA tool resources, functionality, and outputs are

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[7] My Kanta, provided by Kela, is a nationwide patient data repository which offers citizens the opportunity of examining and managing their own medical records. http://www.kanta.fi/en/
[8] Cochrane is an international network providing systematic reviews on evidence from research to enhance healthcare knowledge and decision-making. http://www.cochrane.org/

described in detail in Figure 9. There are three outputs that are illustrated with 1) green dots that indicate interventions the patient in question has received and is eligible to, 2) red dots that indicate identified care gaps reported as decision support reminders suggesting interventions, and 3) blue dots that indicate the health impact of each intervention in the whole population. Basically, Figure 9 illustrates also how the health benefit analyses are described in subsection 2.1.1.

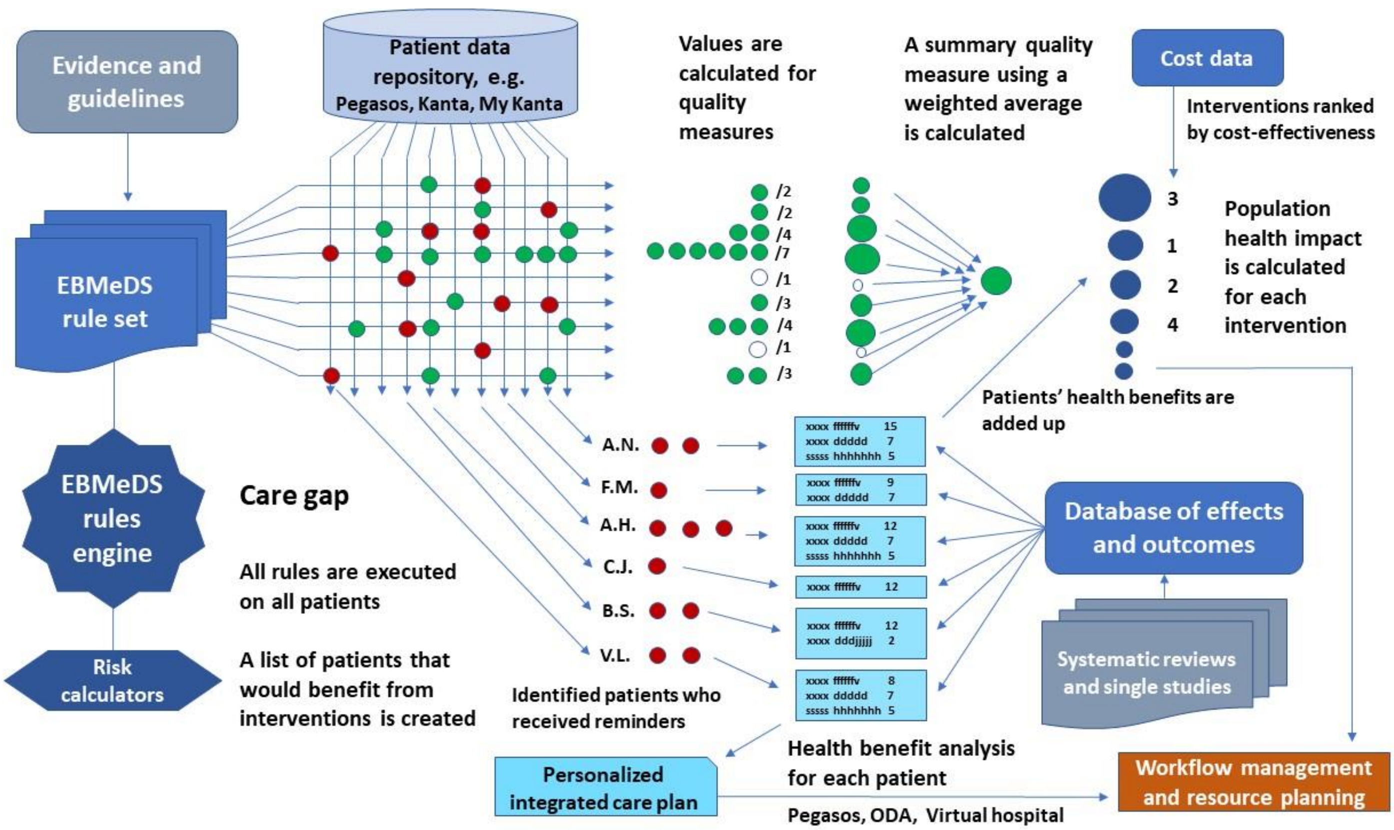

Figure 9. Resources, functionality, and outputs of the Health Benefit Analysis tool (Kunnamo 2017).

The results generated with the HBA tool are currently presented in form of tables (cf. Appendix 1), that are the data interpretation components. For example, a table presenting a real-time report on the individual patient's condition and suggested interventions ranked by numerical values indicating the potential benefit of the respective intervention. Another example of data interpretation component is the table (cf. Appendix 1) consisting of an analysis of health impact of a specific drug for individual patients, who can decide and rank their personal importance of listed health outcomes, both benefits and harms from the drug, and better understand the balance of benefits and harms. A third example is the data interpretation component that provides information on benefits from filling a care gap in a population, that in turn provides meaningful business insights and operational key performance indicators for healthcare service organizers and providers. (cf. Wang et al. 2017: 2 – 3, 6.) However, according to some interviewees, the interpretation of the data could be made more user-friendly by developing the visualization of the results, for example instead of the tables and figures only, present the information also in graphical form that is easier for the users, especially the patients, to understand.

4.2.2. Big data analytics capabilities

The analytical capabilities of the HBA tool can be understood differently depending on the viewpoint. The interviewees' views on the analytical capabilities of the tool vary between the characteristics of descriptive analytics, i.e. business intelligence and different levels of advanced analytics. This is understandable, because the practical experiences of using the tool are still very limited, and the perceptions of the capabilities are based on theoretical conceptions and testing the demo version of the tool. It is expected, that the actual state of the capabilities in terms of the level of analytics are clarified to the users during the pilot use of the tool. Therefore, in this study, the analytical capabilities of the tool are presented and discussed solely based on the perceptions of the interviewees.

The analytics generated with the HBA tool can be considered being on a descriptive level when it is evaluated according to the fact that it is based on data describing what has happened in the past. Although the patient records stored in the EHR system are real-time or near-real time, they are already the past when the analysis is performed. However, it is a matter of professionals to ensure that the patient data used for analysis purposes is fresh enough to be valid for decision-making support or business intelligence. The analytics is considered to represent a *descriptive level* of analytics due to the following statements:

"It shows the current situation by using the information that is being entered to the system, for example what is the patient's condition now and whether all the treatments are correct, or if something is missing."

"The tool that is now being developed is actually beneficial to all players in the sense that it provides this kind of health information to our superiors and managers, and quality information regarding on what kind of care level our customers are, and what we should do to improve it. It helps to plan and develop training, for example, and then on the other hand, there are other benefits as well, when customers benefit from receiving an informed analysis of their own health."

The HBA tool can be claimed to perform *predictive level* analytics when it investigates data and extrapolates a forecast about what is likely to occur, i.e. which health risks might realize. This can be indicated with the following statements regarding the predictive analytics capabilities:

"It utilizes existing algorithms such as the Finnriski algorithm based on large research data from the National Institute for Health and Welfare and the National Public Health Institute to assess how high a person's risk is, for example during the next 10 years, to get a myocardial infarction or stroke, or how high the risk is that he gets ill with diabetes when he knows his risk factor, his waistline, his length and weight, his history, so it can be estimated how high a risk is that he or she will become diabetic. Such risk assessments have been built into the tool."

"The health benefit analysis number itself is already looking to the future in that sense, that it tells, when specific diagnosis and interventions are used, what the expected risks of the outcomes are. In a way, it is comparing the outcomes of different interventions, and what is the probability of a specific health benefit for patients with different interventions."

"Yeah, it's now quite predictive, it's already using some types of calculators, they're found to be good and they work right there, so that's right in that sense."

"It gives some predictions as it comes to the risks, but it does not pose a management plan or risk assessment for the future, that it is a matter of other tools."

However, as some interviewees think, the ranked list of recommended interventions provided as a result from the health benefit analysis of an individual patient, is considered to guide the decision on what should be done, and which interventions and in which order would best improve the health outcome for the patient. As the interventions are recommendations, the patients may, however, choose differently. Also, the results of the health benefit analysis on population level provides the healthcare service providers insights e.g. on how to develop the services and what interventions are offered to whom, so that they are best suited to the needs of the population base. Therefore, as these statements indicate, the analytics capability can be considered being on a *prescriptive level* as well:

"Yeah, there may be a recommendation that if the customer is for example overweight and smokes and has certain risks, that rational treatment for him would be weight control or smoking cessation, and then we can think about how to arrange interventions."

"In my opinion, the greatest added value is that you can give priority to certain things, for example, if you are not ready to do this (smoking cessation) and it does not matter that you will suffer in the event of a complication because you do not consider the importance of this procedure, but you can adapt to it."

"At the population level, when the health benefits of different people are combined – their net benefits – we can see what it is worth to invest in, how we can prevent specific events, or how many such and such patients should we treat to be able to prevent one event."

As indicated above, the levels of performed analytics can be overlapping, i.e. descriptive analytics and business intelligence complemented with features of advanced predictive and prescriptive analytics. Moreover, regarding the analytical capability of the HBA tool, it can be stated that it analyzes big data with varying levels of analytics, without ruling out each other. (cf. Delen 2014: 16.)

It is also evident, that the HBA tool does not, at least at the moment, have any characteristics or features related to artificial intelligence, machine learning or deep learning, e.g. natural language-processing or other learning abilities:

"This is not a machine learning system because it does not itself learn how to operate. Instead, this is based on rules and effectiveness figures that are derived from systematic reviews and applied here. It cannot be called an artificial intelligence either, but rather a rule-based system that, based on these rules, applies this knowledge. Artificial intelligence is characterized by the fact that it actually learns, that is to say, in a way, analyzing what happened to the persons and then changing its reasoning algorithm itself, without any person altering it. Here, this is not the case."

However, when the HBA tool is developed further, and additional, even more complex algorithms and data sources are added to the system, it is possible to reach the analytics levels that are achieved when employing artificial intelligence and machine learning.

"That is the further development, as long as we first get these first algorithms done, then in the future, it will probably be possible to combine artificial intelligence to it, if we want to study bigger masses. Thinking about the population health perspective, people with the same health factors, and when looking for some of the reasons, and as more information starts to come, it would be just natural to associate it with some artificial intelligence that can mine bigger masses of data."

The statement above, is related also to *traceability*, as it refers to data-mining with virtual health checks in order to harvest people having the same health factors, or same patient characteristics and conditions. Traceability is needed when e.g. the health center is aiming to develop the care of specific patient groups:

"It is at least now the goal that we could look at for example children with overweight and see what kind of program we could do for them, or provide alternative anticoagulant therapy for those who are not in balance or who are least balanced on warfarin, and that we could see if a change in medication for those people is needed."

4.2.3. Summary of explanatory variables

In summary, it is evident that the HBA tool fulfills the basic requirements for conducting advanced analytics of healthcare big data. The access to structured qualified patient data is available, as well as evidence-based rules, calculators and rules engine for filtering and analyzing the data. The desired output; prescriptive ranked interventions both for individual care planning and population health management are achieved, as well as business intelligence reports for healthcare service provider's workflow management and resource planning are available.

Moreover, resources such as fact-based decision-making organization culture, committed management and personnel with advanced analytical skills are among the key success factors when conducting big data analytics. Regarding the HBA tool development and piloting, these critical factors are fulfilled. This argument is supported by the clear business need Sitra has identified when deciding to fund the project, the long history that Duodecim has with developing digital decision-support services, the commitment from Saarikka and City of Helsinki in the piloting and development, as well as the fact that SAMK and TUT are already educating new professionals with the needed skills to conduct and interpret health analytics. Spreading the data-driven culture also to the citizens by providing them a possibility to enter their self-measured data for analysis purposes, and engaging them in decision-making on their own care, are strong signs of the new data-driven culture and digital transformation in the society. (cf. Delen 2014: 240.)

The perceptions of the analytical capabilities are varying among the interviewees. The descriptive level is achieved when the results are used for evaluating the patient's current condition based on what is stated in the patient's health records. The importance of entering the data and ensuring its correctness, is emphasized. Also, the usefulness of descriptive level results for the managerial purposes, e.g. quality development, is recognized. Predictive level analytics can be claimed to be achieved when the results are perceived to provide insight to potential health risks, or when the analysis compares the expected outcomes of alternative interventions. Finally, prescriptive level analytics can be claimed when it is possible to give priority to specific interventions, or when it is possible to see what is worth to invest in population health, for example to prevent a specific event of a disease.

The characteristics of the explanatory variables are expected to affect the value co-creation practices and potential benefits, which are analyzed and discussed in the following subchapters.

4.3. Affected or transformed value co-creation practices

In this subsection, the anticipated impacts of using the HBA tool in value co-creation practices, and expected involved actors related to respective example are presented and discussed. The results indicate, with practical examples, how the current value co-creation practices are expected to be affected or reshaped after implementing big data analytics as an actor to the healthcare ecosystem. Compared to the examples of the practices presented in the BDET model (Table 3), it can be stated that the empirical data contains some similarities, but also introduces completely new, HBA tool specific practices in the value co-creation. A summary of the affected value co-creation practices is presented in Table 7.

Table 7. Value co-creation practice sub-elements affected by using the HBA tool.

Value co-creation practice	Example of affected sub-element	Expected involved actors
Meaningful use of EHRs	Ensure that correct patient data needed for the analysis purposes are entered into the EHR system in structured format	Health professionals
	Achieve a comprehensive and up-to-date view on the patient's health in order to provide the right care	Health professionals
	Act proactively based on virtual health checks of the population, and invite patients in need to visit health center for further examination, individual care planning and treatment	Health professionals
	Trace and find undertreated and overtreated patients, as well as useless treatments or medications	Health professionals
	Detect specific trends and behavior related to population health	Health professionals Healthcare managers

Evidence-based medicine	Explore the facts from medical events or patient treatments to improve specific outcome	Health professionals
	Build holistic view of evidence by insights from literature-based data and research studies, such as EBMeDS and Current care guidelines	Health professionals
	Select together with the patient the most suitable intervention from the evidence-based ranked list	Health professionals Patients
Multi-disciplinary cooperation	Improve the care planning and care process of multimorbid patients	Care managers Hospitalists Social workers
	Provide joint decisions regarding treatments to patients from a multidisciplinary team	Care managers Hospitalists
Clinical resource integration	Allocate health service (monetary) resources as indicated by population needs	Healthcare service organizers
	Allocate health service resources to reduce indicated care gaps in selected patient groups	Healthcare service providers
	Self-evaluate the need for health service or intervention with the provided analytical tools and platforms	Patients or their custodians
Network collaboration	Create cross-boundary practices	Health professionals Social workers Schools Associations Patients or their custodians
	Lower the threshold of raising patient issues and facilitate discussion and decision-making between professionals and stakeholders	
	Build a common understanding of provided healthcare services and needed interventions	
	Prioritize interventions between specialties	Health professionals

Network knowledge creation	Share knowledge about service guidance across sector boundaries	Health professionals Social workers
	Collect all data in one place for centralized information sharing and analysis purposes	Health professionals, e.g. Health analysts
	Learn which interventions the patients value and prefer	Health professionals Patients
Personalized care	Create personalized disease risk profile and integrated care management plan for each patient	Health professionals e.g. Hospitalists or Care managers
	Make shared decisions on interventions proactively	Health professionals Patients
	Influence in own care by evaluating and choosing between recommended interventions	Patients

As indicated with several detailed examples, each value co-creation practice is affected due to involvement of the HBA tool. The evolutionary-level value co-creation practices (cf. Wang et al. 2017: 2 – 3) such as meaningful use of EHRs require paying attention to ensuring the quality and format of the patient data and evidence-based medicine and the timeliness of the evidence enabling the accuracy of the analysis results. The tool also enables completely new practices such as virtual health checks and tracing patients with hidden needs, which aims to narrowing the indicated care gap. Additionally, the tool enhances internal integration as it enables more effective multidisciplinary collaboration in mutual care planning and decision making.

Regarding the revolutionary-level value co-creation practices, (cf. Wang et al. 2017: 2 – 3), business process redesign is indicated in form of clinical resource integration which is affected by the HBA tool as it enables improvement in allocation of healthcare resources and targeting the monetary resources to interventions which are proved the be most beneficial on the population health level. Business process redesign is in question also when individual patients learn to practice self-evaluation and self-care before contacting health centers. That in turn provides an opportunity to target the healthcare resources for those who benefit more from it. Moreover, business network redesign is indicated in value co-creation practices regarding network cooperation and knowledge creation. They are affected by the HBA tool as it is expected to enable to improve, and even create new, cross-boundary collaboration methods both in creating and compilating patient information, as well as sharing it for cross-boundary planning and decision-making.

The most game-changing revolutionary-level value co-creation practices which lead to business scope redefinition are related to the personalized care. The HBA tool enables making accurate personalized care plans based on a patient's disease risk profiles. It also creates completely new practices, where the patient becomes an important actor and essential value co-creator. The tool provides an opportunity to a major change in the current practices where health professionals, especially doctors are solely responsible for decision making and risk bearing regarding the selected interventions and health outcomes (cf. McGuire et al. 1988: 39; Jung & Padman 2015: 302). These value co-creation practices are changing the current set up between the health professionals, especially doctors, and patients. The health benefit analysis offers the patient an opportunity to evaluate the health benefits or harms of the recommended interventions and freedom to make an informed choice between them.

The indicated examples of respective value co-creation practices are analyzed and discussed in more detail in the following subsections.

4.3.1. Meaningful use of electronic health records

Patient health data has traditionally been entered and stored in electronic health records and databases, which are continuously fed with new data, and which ultimately are left unused. The stored data has not been considered useful until the patient gets ill and next time visits the health center or hospital, where the doctor then checks what kind of health issues the patient has suffered from before. Now, with the HBA tool, the use of the EHRs is expected to become more meaningful as the patient data is used, together with decision support systems, in a more proactive manner, which is expected to be useful for several stakeholders. However, to get valid results, it is essential that the patient data is without unnecessary delays recorded into the EHR system in a structured format. This directly affects the value co-creation practice as there now is a managerial need to plan and agree between professionals about who and how to deal with this requirement. (cf. Sivarajah et al. 2017: 265.) The following statement supports this:

“First of all, it is important to have correct information in correct format in the EHR system, which, however, may mean additional work, e.g. blood pressure, smoking habits, medication and diagnostic information (e.g. coronary artery disease) must be up to date.”

Because the EHR system is now expected to contain more and correct information about the patient, the HBA tool enables achieving comprehensive and up to date view about patient’s health and improves the possibility to provide correct treatment:

“After that, the doctor can get an overall picture of the patient. He can get suggestions for decision support on how to treat the patient. He also can see the health benefit analysis, from which he can see which interventions would most benefit this patient, as well as which might be less beneficial for him.”

It is often the case, that patients have hidden needs for a treatment or that they may benefit from having a specific medication. These needs may be discovered only randomly when a patient visits a doctor for another reason. Therefore, virtual health checks conducted with the HBA tool on EHR records of a selected population in order to find patients potentially in need for treatment of medication, are changing the current reactive practices into more proactive value co-creation practices, where the tool generates lists of patients by specific conditions. The list can help in tracing the undertreated patients, as well as possibly overtreated patients, and by that means reduce the indicated health care gaps. (cf. Wang et al. 2017: 7.) The following statement describes this practice as follows:

“We are talking about proactive activity, for example, when a person has been exposed to health risks, a professional may take the initiative and contact this person to discuss whether he or she would be willing to visit the reception or start some treatments. So, preventive action instead of waiting for someone to reserve time from the reception.”

“It helps to find undertreated patients, but also those who are overtreated. There may be some medication or treatment that the patient uses unnecessarily, or there may be such treatments that this patient should not use at all, but instead should use something else. So that kind of insight can be obtained from EHR.”

The HBA tool also enables the detection of specific health and behavioral aspects of the population from the EHR system, which has not been possible earlier because of lack of data or useful summaries. Now, decent summaries that are enabled by the health benefit analysis conducted on the population level can support in decision-making aiming to reduce health inequalities, for example in the development of specific health services in the area:

"We currently do not get any data right out of our systems. We have only a vast collection of information about our clients, levels of care and diagnosis, but no decent summaries", and further *"the HBA tool can open up the vision, once we get better data and we see e.g. that smoking in some areas is higher than in other areas, so it might be worth to invest more in smoking cessation interventions there, than in another area."*

As recording and analyzing the data means work, in future, this could be the task of the health analysts. They could be responsible for collecting and analyzing the EHR data and providing the results for e.g. prioritizing and rationalizing the operations. However, they need a mandate to use the data and overall, be part of the care team.

4.3.2. Evidence-based medicine

Evidence-based medicine is already practiced in health centers that now are piloting the HBA tool. They have experience with Current care guidelines and EBMeDS, which both are built on wide medical evidence such as Cochrane reviews, meta-data-analyses, latest research, and literature. According to the current practices, the evidence-based support systems may, for example, provide an automatic notification about medical incidents, where the doctor needs to pay attention to something critical regarding the patient's medication. Health professionals can also get feasible insights and recommendations from these systems without specifically asking for it, as indicated in the following statement:

"Currently, the decision support means that even without anyone actively searching information, it automatically displays messages, and suggestions on how to treat the patient."

The health benefit analysis algorithm is designed to use the evidence in these systems and combine it with the patient data retrieved from the EHR. The objective is, that the tool provides a user-friendly view to the patient's health and suggested evidence-based interventions. It generates, unlike the current systems, a ranked list of the most suitable interventions for the individual patient to choose from, and by that means enables new ways to health professionals for co-creation of value with the patients. In future, when the tool is developed further, some interviewees expressed their wish that amount of data further increases and that also some artificial intelligence related features could be developed, perhaps a common system for the whole country.

"Decision support notifications have been more fragmented listings, and they have not evaluated separately what might be the most useful intervention. In that sense, of course, the evidence-based medicine is increasing, and the tool makes it easier to use."

"Of course, the artificial intelligence is as good as the data mass that it has at its disposal. If we could get all the information for common use, that would be great."

However, it is expected that the relation between the health professionals, specifically the doctor, and the patient, needs to be clarified in terms of what is really the mandate of the patient to choose an intervention he or she prefers. For example, it should be decided whether the patient is allowed to choose the most expensive intervention, even it is not ranked to bring the best health outcome, or how should the interventions be chosen if the patient is not mentally mature enough to take this decision. What kind of value co-creation practice would suit best for this kind of situation need to be planned and taken into use, as expressed in the following statement:

"One has to think about what is happening when a patient wants, for example, a very expensive intervention, but the benefit of which is estimated to be reasonably small in that situation. Then one also must think if a professional can refuse to give you any intervention, just say that okay sorry, but you are not given that treatment now. It is a bit too expensive for you to get it. This is probably the biggest challenge. Transparency is a good thing, but are both professionals and customers willing to receive new stuff?"

4.3.3. Multidisciplinary cooperation

Multidisciplinary cooperation is traditionally coordinated in health centers by work pairs consisting of a patient's personal doctor and personal nurse. In future, there could be a new role, a specific care manager, who is responsible for the holistic planning and coordinating of an individual patient’s care. So far, there has been a lack of tools for this and it has therefore been hard to maintain individual care plans, but this is about to change. (cf. Batalden et al. 2016: 509.) Moreover, the HBA tool is seen useful when there is a need for flexibility, e.g. when planning interventions for multimorbid patients, such as the elderly having many parallel health problems. Also, in cases where there are many service providers and actors involved in the care, e.g. from the social sector, or associations, it helps when there is a tool that is able to provide a comprehensive view of the patient’s situation.

“The HBA tool is also used when certain patients, such as substance abuse and mental health patients, need flexible operating models. There are also many different actors involved in the care of the elderly, and families with children. In a way, this tool gives a common medical aspect that everyone can take advantage of and get a similar perspective on the patient.”

In hospitals it may be more complex, since each medical doctor consults only on his own area of medical specialty. It is anticipated, that a new doctor specialist role, so called hospitalist, are soon introduced to the Finnish hospitals. Having hospitalists is already quite common in the US hospitals. They are generalists, who manage the overall treatment of the patients, and when needed, request a consultation from the doctors representing the other narrow medicine specialties. The HBA tool would be perfect in that sense, as the hospitalists could use it for conducting health benefit analyses and plan and coordinate the patient’s care process in the hospital, as indicated in the following statement:

“Of course, their job involves then conducting the health benefit analysis and thinking about which of those special medical care would be important to this patient. It is a tool that anyone can use, regardless of the specialty. The results of a health benefit analysis are understandable in such way that a representative of any specialty or professional group can take advantage of the results.”

The multidisciplinary cooperation and joint decision-making between specialties in hospitals, including social factors, can be improved significantly with the HBA tool and the new roles of care managers and hospitalists. Health analysts could also have a role here in future. However, it is evident, that only introducing new tools and systems is not enough, but also the related roles and processes, for value co-creation, need to be addressed.

4.3.4. Clinical resource integration

Using advanced analytics provides good insights on planning resource allocation in healthcare services, both for the healthcare service providers and for the healthcare service organizers, operating on macro and meso levels in the healthcare ecosystem (cf. Frow et. al 2016: 27). As these actors seek to reduce inequalities in the population and to narrow health care gaps, the HBA tool is useful as it helps to indicate and analyze the needs of the specific patient groups within the population and at a proper allocation of health care resources.

A good practical example on this is the need for reducing the smoking habits of a specific group, as the health center management can get insight on the issue for planning how and with which resources it is most effective to intervene the situation:

"Individuals who would benefit significantly from tobacco weaning are searched from the population. Then tobacco weaning is organized to everyone wishing for it. In this way, we try to identify the resource needs, for example what resources and what interventions should be made. When identifying how many customers need this intervention, we can calculate how much of the nursing staff's work time need to be allocated to the provision of tobacco weaning services."

If the implemented intervention is successful, it is possible to indicate with the HBA tool its impact on the health outcome of this specific population. In this way, the healthcare service providers and organizers can get feedback on the success of the intervention they invested resources in. In addition, it provides insight and information on rationalization of operations and further development of resources. Moreover, when an individual or group of patients succeed to stop smoking, the potential health outcome is shared with the healthcare service providers as they now can allocate resources for other patient groups.

Also, as the healthcare service customers are seen as active actors of value co-creation, it would in future be desirable that they, before contacting health centers, conduct a self-evaluation of their current need for health service and intervention using the provided analytical tools and platforms for the purpose. Only in case there is a health problem, which requires a specific intervention, the patient is offered an appointment at the health center. In this way, it can be claimed that patients contribute to more effective resource allocation of healthcare services.

4.3.5. Network collaboration

It is anticipated that using the HBA tool across the health and social sector boundaries would be a very good improvement in the current siloed operations but requires paying attention to legal matters and regulations on the higher levels of the ecosystem (cf. Frow et al. 2016: 27). The multisectoral cross-boundary network cooperation (cf. Triple Aim, Kindig & Isham 2014: 3) would benefit all actors in value co-creation and be more cost-effective, but the current practices evidently need to be transformed, and new ones created with careful planning, ensuring that the legal aspects are fulfilled, and citizens' privacy treated in a most cautious manner. This concern comes up the following statement:

"If healthcare is difficult, social work is even more difficult because there are so many legislative obstacles making it so siloed and hierarchical, that there are even bigger problems than on the healthcare side. So, there is room for development and it would be quite brilliant if such tools were used to change the operating model. It is of course regrettable that for example child protection issues are really difficult. That is why legislation is understandable and somehow seems impossible to reform, if some lawyers say something. But if we get their understanding, then we have to make that change."

The use of the HBA tool enables also the lowering of the threshold of raising patient issues and facilitates discussion and decision-making between professionals, for example between doctors and nurses, and between health professionals and representatives of the social sector, e.g. social or home care workers:

"It facilitates cooperation between the professional groups as I have discussed for example with the home care workers. It works as a tool giving them the opportunity to have a better

conversation with the doctors. Now home nurses can more confidently propose for example some changes in medication or treatments that they have found necessary. Before, it was more like a gut feeling, but now the tool provides a little more robust approach to the nurses to present their opinion. They can now be more confident to point out which are the health benefits, and whether a drug needs to be exchanged, or what should be done."

In the care-cycle of one patient, there might be many health professionals involved, as well as professionals from social or school sectors. Family members also have an important role if the patient is a child, or another, often older, family member suffering from multiple diseases. However, since the patient is the starting point of the care, and set in the focus of the health service, it is important that all actors in the network can build a common understanding of the provided healthcare service and needed interventions. This is brought up in the following statement:

"In network cooperation, the issue has been resolved so that the patient is at the center of the activity. The information is personalized and targeted to that person, including any risk factors. That is, of course, better than having the information scattered in different places."

With the help of the health benefit analysis results and integrated care planning it is possible to prioritize the needed interventions and decide the order in which interventions should be carried out so that the recovery of the patient is as smooth as possible, and the health outcomes are successful (cf. Porter 2010: 2478; Nordgren 2009: 124). For example, if an elderly patient needs geriatric rehabilitation and several major interventions from different specialties, e.g. a hip surgery and a cataract surgery at the same time, it is essential, that the network cooperation between the specialties is working smoothly, as expressed here:

"For example, an ophthalmologist orders a patient to cataract surgery. However, the patient is also in queue for hip surgery and at the same time waits for a geriatric rehabilitation period somewhere. Now, it is worthwhile to prioritize and plan carefully whether the cataract surgery is reasonable before the rehabilitation period, or before the hip surgery. This is important in order to prevent the risk that with poor vision ability the patient may run into thresholds and crash."

4.3.6. Network knowledge creation

The current plan is to include in the health benefit analysis some variables from the social side as well e.g. information on a patient’s employment status, area of residence, need for social services and other relevant social factors. Adding these variables to the analysis provides a possibility for more accurate results regarding the recommended interventions, which again lead to additional benefits and even better health outcomes. Therefore, the HBA tool will enable sharing knowledge about a patient’s service guidance across sector boundaries (cf. Kindig & Isham 2014: 3):

“Of course, one would like it to become a tool for social work as well. That would work just fine if we get some variables from the social side as well, then it could work on that side too.”

“Yes, for example, in a service guidance unit that defines which unit takes the responsibility of further care of the patient. In the service guidance unit there is a wide range of experts in the field, who in that sense try to build a picture of both the social care and the health care needs of the patient. In that sense, this brings one more tool to them as well.”

Most of the patient data is currently scattered which makes it difficult to gain a comprehensive view on a patient’s status. The HBA tool can motivate the actors to organize this better by collecting all data in one place for centralized information sharing and analysis purposes (cf. Health Level Seven 2013: 6 – 7). For the time being, this is a task that could be carried out e.g. by the health analysts:

“A health analyst could make a patient summary, meaning that they would collect the information from where they are now scattered and this tool (HBA) would be one part of it. That is, this kind of health benefit analysis would be one thing, and then there could also be some medical images so that the whole summary is ready, i.e. what treatments have been made and what allergies the patient has. I believe doctors might think it would be beneficial as they would get a summary, so that they do not have to first open ten different computer programs to get the information.”

Using the HBA tool and conducting health benefit analysis, and discussing the results with the patients enables discovering new knowledge regarding the patient's preferable interventions:

"Yes, it is likely that new information will be formed, at least as to how the patient himself evaluates the health benefits and the side effects of different therapeutic methods on his health and well-being. That is, we get information on at least patients' attitudes and opinions."

Practices where new actors, such as health analysts, and additional information from other sectors are introduced, require, however, a change in the current approach in the relationship between the doctors or other health professionals and the patient. Also, discussing more openly about the optional interventions with the patients means that the healthcare services may become more accessible than before (cf. Nordgren 2009: 121).

4.3.7. Personalized care

Traditionally, a patient has been treated with interventions ordered or recommended by doctors or other health professionals. Moreover, the doctors have been responsible for the decision-making and risk-bearing for what kind of care and which interventions a patient is offered (cf. McGuire et. al 1988: 39, 46, 48). Personalized care, in turn, is more patient-centered practice where the patients themselves are involved in the care process. One of the key features of the HBA tool is, that it supports the integrated personalized care practices by providing insight to the most beneficial interventions.

In order to be able to recommend the most suitable interventions and achieve the best possible health outcomes for a patient, health professionals need to know, among other things, the disease risk profile of the patient. Therefore, the doctor determines the baseline risk of the patient (cf. Appendix 1). When the baseline risk is known, the HBA tool enables achieving more accurate and personalized disease risk profiles of the individual patients. This practice also produces valuable information for integrated care planning for each individual patient. In future, it is, however, needed and expected that additional risk calculators as well as e.g. genome data are added to the tool, which enables analyzing even a broader disease spectrum and gives a possibility to enhance the personalized care even more. It can be concluded, that the current practices regarding personalized care are in progress of continuous improvement as the HBA tool is developed further with additional algorithms and data sources:

"We need a lot of information about the patient's risk level, for example what is the patient's baseline risk. We already have risk calculators, but we need a lot more. That is, we should find the best prognostic evaluation tools and algorithms in the world and utilize them."

"I think it (personalized care) will improve, but it is not entirely clear what kind of information it can be based on. In particular, if genetic data is added at some point, it certainly means a personal approach."

The results of the performed health benefit analyses provide a good basis for discussion between health professionals and patients how to act proactively in order to ensure the best possible health outcomes for the patient. Moreover, the evidence-based discussion enables shared decision-making regarding the interventions. The result of the analysis and discussing it with the health professional, provides patients the opportunity to influence in their own care by choosing between recommended interventions. (cf. Batalden et al. 2016: 509) These value co-creation practices are indicated for example in the following statements:

"When a customer can rate and value evidence-based interventions themselves, one can start implementing an intervention that he or she is motivated to accept and that he / she sees relevant, for example smoking cessation or something else. With this tool, you can quite concretely show the effect of the smoking cessation, or if we give this and that medicine, it will have that effect. It is, in fact, something more tangible."

"The tool calculates the benefits and harms, for example, if I as a patient decide that I do not want this medicine because it has these side effects, it calculates the benefits in relation to the harms."

"This is a crucially important issue for personalized care, for example, when talking about self-care in long-term illnesses, I personally see that the customer is one of the actors of production, one of our resources that implements and influences the effectiveness of professionals. So, in that sense it is extremely important."

Being able to provide such information and decision power to the patients is new and innovative (cf. Jung & Padman 2015: 302). It is expected that when the HBA tool is developed further, it can provide evidence-based recommendations on interventions to patients having different diseases and involve them in value co-creation, and that is even more revolutionary. It is also anticipated that the tool will encourage the health professionals to act more proactively and use it more actively in care planning.

4.3.8. Effects in healthcare ecosystem actors

Introducing the HBA tool, or more specifically the algorithms it employs, to the healthcare ecosystem effects not only the value co-creation practices but means also changes in the responsibilities of the existing staff, as well as creates a need for completely new roles and professions. It can be claimed, that this is an exemplification of how digitalization and data-driven culture changes the traditional organization, professions, and practices on all levels. Utilizing advanced analytics in healthcare requires competence development of the healthcare professionals and their management, as well as professionals closely involved in the care cycle, such as social workers. For example, to get the best possible results and health outcomes with the HBA tool, the professionals need to understand the importance of structured patient data, learn how to produce, and store it correctly, they need to have skills to conduct the health benefit analysis, interpret the results and facilitate the discussion with the patients. However, conducting the health benefit analyses with the tool, does not require any specific technical or mathematical skills, but it helps if the user understands the basics of statistical methods and is able to explain how the results are generated, i.e. why a result is what it is. The healthcare managers and actors on the upper levels of the healthcare ecosystem need to understand what the implementation of such tools and advanced analytics requires from their side, i.e. commitment to the data-driven solutions and selected tools, and alignment with business and IT strategies (cf. Delen 2014: 240).

The mentioned new roles in the healthcare service provider organizations are hospitalists, care managers, and health analysts. Hospitalists are doctors taking the overall responsibility of the specialized medical care process of a patient in hospitals, which is already a common practice e.g. in the US. Care manager, in turn, is a new role which can be carried out also by current health professionals. A care manager can be for example a nurse who is responsible for coordinating the patient’s care and care planning in a health center, and possibly across sector boundaries. A completely new profession is the so-called health analyst, intended to act as a professional conducting health analytics, interpreting the results, as well as explaining and discussing the results with the patients. To educate health analysts, SAMK in Finland and Tallinn University of Technology in Estonia have initiated a pilot program training health and social care professionals with various backgrounds to become health analysts. Most of the health analyst students are currently working in health centers, hospitals or in social sector in different roles, so they are in a key position when introducing this new profession to the organizations, and to the patients.

Patients are also considered to be part of the healthcare ecosystem on the micro level (cf. Frow et al. 2016: 27). Now, when moving towards data-driven culture and using the HBA tool to improve the personalized care through health benefit analyses, the role of the patient becomes more active as they are given the chance to evaluate and choose which intervention they are ready to take (cf. the personalized care in the previous subsection). If the chosen intervention is for example smoking cessation or weight control, it means that the patient has a crucial role in value co-creation in order to achieve the desired outcome. Using the tool or understanding advanced analytics is not a requirement for the patient but committing to the chosen intervention is.

4.4. Potential benefits and performance

The potential benefits achieved by conducting health benefit analyses with the HBA tool are studied through examples falling into operational, managerial, strategic, organizational and IT infrastructure benefit dimensions. The potential benefits revealed in the interviews are further categorized into performance that generate value for individual patients, value for population health, and business value for healthcare service providers or organizers. The identified expected benefits of respective dimensions, and their value generated to the determined stakeholders are summarized in Table 8.

Compared to the benefit dimensions and examples of subdimensions presented in the applied BDET model (Table 4), the empirical data verifies a number of operational, managerial, strategic, and organizational benefits generating value for the healthcare service provider. However, due to the nature of the HBA tool, most of the suggested IT infrastructure benefits are not realized. Moreover, due to the fact that the BDET model was complemented with individual patients and population health, some additional benefits and value generated for these stakeholders, are identified.

Table 8. Expected potential benefits and performance that generate value to stakeholders.

Benefit dimensions	**Indicated expected benefits**	**Value generated to**
Operational benefits	Improved workflow efficiency Productivity improvement Cost reduction Improved and accelerated use of information Quality monitoring Target treatments to those who benefit most	Healthcare service provider Population health
	Accuracy of clinical decisions Improved health outcomes Active participation in own care Influence in selected interventions Improved customer experience	Individual patient
Managerial benefits	Improved care planning and decision-making Improved performance Improved allocation of resources Business intelligence Improve direction and management of staff Improve employee satisfaction	Healthcare service provider / organizer
	Reduce health inequalities in the population Narrow the discovered care gaps Prevent cases of overtreatment	Population health Individual patient
Strategic benefits	Facilitate discussion among decision makers Gain comprehensive view for meeting future needs Contribute shift to value-based healthcare Implement the selected vision and maintain focus Build competitive advantages Build new business innovations and alliances	Healthcare service provider / organizer

Organizational benefits	Improve team work Cross-functional communication Solve multidisciplinary problems quickly Organizational learning from clinical reports Process and quality development Learn to know the patients better	Healthcare service provider
	Ensure seamless patient experience	Individual patient
IT Infrastructure benefits	Better use of existing healthcare information systems, e.g. supplement EHR Improved information gathering and sharing	Healthcare service provider
	between actors with extended access rights	Individual patient

4.4.1. Identified benefits

In each benefit dimension there are some specific expected benefits which are presented and discussed in more detail in the following paragraphs. Several of the reported potential benefits have been revealed already in the answers regarding value co-creation practices, and some are identified through presenting statements to the interviewees.

Operational benefits

It is revealed, that with the HBA tool it is possible for the healthcare service provider to obtain several operational benefits, such as improved workflow efficiency and productivity, as well as cost savings. All these are mainly achieved through the proactive approach to the integrated care planning and interventions because it is more effective to treat patients before they get more severely ill. The HBA tool also enables accelerated use of population health data and clinical information which further improves productivity of the operations and the effectiveness of health outcomes. (cf. Nordgren 2009: 124.) Further, it enables improved operational quality monitoring, which so far has not been possible to this extent. It also contributes to the quality and accuracy of clinical decisions. Both quality monitoring and accuracy of clinical decisions are considered significant core issues in health benefit analyses. These statements confirm the mentioned operational benefits:

"It is a benefit, if care operations can be rationalized and arranged according to the needs."

"The tool makes you also ponder internal processes and avoid possible bottlenecks."

"Quality monitoring, and the accuracy and quality of care decisions are essential core issues, and there is lot of room for improvement."

"As the tool enables patient data analysis even once a month, it is possible to plan and implement any quality improvement measures and monitor their effectiveness."

Quality monitoring is achieved through the tool-based metrics and controls, as well as quality benchmarking between care units. Additional operational benefits can be generated through health benefit analyses in order to provide insights on how to target interventions and treatments to those who benefit the most, which is beneficial from the population health point of view. It also helps with finding new views on potential treatments and personalized patient care. Customer experience is improved as patients now are considered active actors in value co-creation, e.g. using the HBA tool enables more personalized care practices and it increases transparency as the patient is offered a chance to choose between interventions and participate in shared decision-making. (cf. Payne et al. 2008: 93 – 94.) This is expected to be valuable to the patient and lead to increased customer satisfaction. (cf. Batalden et al. 2016: 509.) The following statement sums up the operational benefits regarding the customer experience:

"The ability to influence your own care will definitely bring a better service experience."

Moreover, access to the operational benefits is supported by the easiness of using the existing knowledge and applying evidence-based care with the tool.

Managerial benefits

The HBA tool is expected to generate managerial benefits to the healthcare service provider, e.g. in providing information and views on planning and resource allocation, which again improves performance. It can also act as a tool for prioritizing health care resources for producing the needed services for those who benefit the most from them, and that generates value for the individual patients and population health. It that sense, the health benefit analyses can be considered business intelligence, that gives the management information on, what kind of health services are needed in the population in order to reduce the health inequalities and discovered health deficits. (cf. Airoldi et al. 2014: 970; Kunnamo 2016: 69.)

"The tool gives background information about the population base to whom services are produced, it is a kind of business intelligence."

Another expected managerial benefit is related to the direction and management of staff and improved employee satisfaction. These benefits can be achieved as the HBA tool enables the leading doctors to direct and guide their subordinates in their work and to facilitate the value co-creation between health professionals and patients. Moreover, the tool is expected to improve employee satisfaction, as the healthcare professionals can gain more meaningfulness in their work since they now can find the right evidence-based interventions that are predicted to work for the respective patients, and which are proved to be beneficial:

"This is also meaningful for employees because they are now better able to find interventions that are useful to patients."

Strategic benefits

Implementing and using the HBA tool provide several strategic benefits for healthcare service providers, such as public or private health centers and hospitals, but also for the healthcare service organizers that are operating on the upper levels of the healthcare ecosystem. These actors are the state health authorities such as local provinces responsible for steering public funding and organizing the healthcare services. For example, the health benefit analysis performed on population level, can facilitate discussion among decision makers e.g. regarding the future development and organizational planning of health services in order to reduce health inequalities among population. Moreover, in case the healthcare service organizer's or provider's strategy is targeting to shift to value-based healthcare (cf. Cosgrove 2013; Porter & Teisberg 2006), the HBA tool can provide valuable insights for reaching that goal as well. To implement the selected vision and maintaining the focus, for example preventive care can be supported with the HBA tool as it offers evidence-based insights into proactive care and interventions. The following statement describes the intentions to shifting into more value-based measures:

"It is expected, that it can be agreed with the decision makers regarding the current service descriptions, which now are based on quite quantitative measures, that they are complemented with measures of effectiveness."

The HBA tool contributes to achieving business competitive advantages by using advanced analytics and business intelligence as a differentiator. When people are offered the freedom to choose where they want to consume their health services, it is obvious that the possibility of personalized care planning and optional interventions are expected to attract patients to acquire health services from a health center that can guarantee better health outcomes by providing health benefit analyses, and proves it has the latest health technology solutions at its disposal. This ensures accessibility to qualified health services for the customers of the smaller health service provides as well. The HBA tool with its evidence-based analytics is an important differentiator for gaining competitive advantage especially for small health centers which compete against bigger health service providers employing a greater number of qualified healthcare experts, and therefore gaining competitive advantages:

"I think that if you have the latest technology, it is a kind of competitive advantage, especially for a small health center. It means access to a big data mass, which is a great thing."

The HBA tool, especially when more new knowledge is gained on the effectiveness of the interventions, enables building also new innovations (cf. Groves et al. 2013: 7):

"The tool provides a starting point in which we have information about the effectiveness of interventions and what is important. On this basis, it is good to build new operating models, practices, and tools."

The innovations can be new operating models and practices related e.g. in the patients' freedom of choice, or new tools that can be built in cooperation or in strategic alliances with other public and private healthcare actors.

Organizational benefits

It is indicated, that using the HBA tool generates numerous organizational benefits as well. It is revealed that it can improve team work and cross-functional communication, especially when e.g. a health analyst is available to facilitate the cooperation. Also, multidisciplinary problem solving is supported when doctors use the results generated with HBA tool at their meetings to plan how they can achieve the desired effectiveness and set goals. Organizational learning can be achieved for example when the analytics and statistical knowledge regarding patients and population is being used as business intelligence for process development and quality improvement. The tool enables and supports the development of specific quality metrics for the purpose. Moreover, it can be claimed, that organizational learning also happens when health professionals teach each other and learn to know their patients and their healthcare service needs better, which in turn leads to improved patient experience. (cf. Demirkan et al. 2015: 734.) The following statement indicates how the introduction of the HBA tool has kicked off organizational learning process:

"Yes, this has already kicked off a lot of discussion and dialogue and ideas about how people in their own work and in their own workplace could act as an organization. For example, doctors have planned how they could train each other and what kind of support system has been built for them."

IT Infrastructure benefits

The HBA tool is built in as an additional new feature in the existing EHR systems, so it supplements rather than replaces or adds on other IT systems. Therefore, it is not relevant to expect it to generate any specific cost-related benefits either at this point. It enables, however, a chance to improved information sharing between the health centers and hospitals, as well as with patients, provided that the access rights to the health benefit analysis results are granted (cf. Appendix 2: 1). The following was stated regarding the IT infrastructure benefits:

"This is a complementary system that does not replace anything. In a way it enhances the use of existing systems."

"I do not think it affects IT costs. Most probably it has an impact on treatment costs once we get the right patients in the right place at an earlier stage."

4.4.2. Value generated to stakeholders

Based on the discovered benefits discussed above, it can be stated that the value promise of the HBA tool and performed advanced analytics arise value for the stakeholders as follows:

Business value for the healthcare service providers and at some cases additionally for the service organizers arise through all benefit dimensions. Value is prominent in strategic issues, such as in gaining competitive advantage through differentiation, support for additional innovations, and in contributing the shift into value-based healthcare (cf. Porter & Teisberg 2006:8; Cosgrove 2013) where the definitions of value is based on the betterment of the patient's health (cf. Rantala & Karjaluoto 2016: 34). In addition, utilizing the business intelligence generated by the tool in high-level strategic decision making and long-range planning, create business value for the managerial, operational, and organizational activities. Moreover, as there are no significant benefits regarding the IT infrastructure, the business value of the HBA tool can still be considered positive, as it acts as a complementary system that helps to get more out of the existing systems.

The *value generated for individual patients* can be specified as the value-in-use (cf. Vargo et al. 2008: 146; Grönroos 2008: 298, 304), that arise especially due to the significant new modes of interaction. In such interaction the digital actor, i.e. the health benefit algorithm, and the patient are considered being part of the health ecosystem (cf. Frow et al. (2016: 27), and therefore active actors in value co-creation. (cf. Rantala & Karjaluoto 2016: 40.)

The value for the individual patients can also be claimed due to the freedom of making informed choices among recommended and ranked interventions, as well as transparency in seeing the possible care paths, and shared decision-making (cf. Nordgren 2011: 309). This is different from the traditional care practices where the health professionals and doctors have been in the position to decide what treatments are recommended in the first place, and which services patients are eligible to.

Moreover, due to the possibility of conducting virtual health checks in the population, the individual patients can achieve value as they are proactively found and invited to further health examination and offered needed health services. This means that individual patients can avoid undertreatment by getting accurate and evidence-based diagnosis earlier and the needed interventions in good time, compared to the situation where they seek help only after getting more severely ill.

The value generated for the individual patients is expected to improve even more when the analyzed big data is added with the patients' self-monitored data gathered e.g. from various wearable devices or genome databases (cf. Demirkan et al. 2015: 735; Sakr & Elgammal 2016: 50). The wider range of data enables receiving more specific information about the possibility of getting a particular disease. It also enhances the patient's awareness of belonging to a certain risk group and gaining understanding on how own decisions effect in own care in practice. Moreover, it may even reduce the false perceptions among patients regarding the effectiveness of specific interventions (cf. Frow et al. 2016: 24, 26).

In order to achieve the stated value, individual patients are expected to provide honest information about themselves and their health. Health professionals should take into account that people tend to embellish the information regarding their lifestyle habits, for example smoking habits, which may lead to incorrect health benefit analysis result, and therefore lead to unsuitable recommendations of interventions. It is assumed, that most people are interested in their own health and willing to take responsibility in own health care by committing to the recommended interventions. Therefore, mutual trust is also needed. It is, however, possible that some people do not see value in this and completely refuse to have their personal health benefits analyzed. This should be respected as sharing own health data is voluntary, and it is also possible that people are not mature to assimilate this kind of information.

With the above said, it can be concluded that health benefit analysis performed with the tool, generate value for the individual patients according to the customer service logic (cf. Grönroos 2008: 298) and in accordance with the five axioms presented in the latest research regarding S-D logic (cf. Vargo et al. 2008: 148; Vargo & Lusch 2017: 47; Lusch et al 2016: 2957).

Value for the population health is generated by reduced health inequalities, and by providing more cost-effective and better health services to the right people who need and benefit the most from them. Better targeting also prevents the use of healthcare resources in cases where no intervention or action is required. Moreover, value is generated when identifying regional health risks and developing health services to reduce those risks. (cf. Kindig & Stoddart 2003: 381; Kindig 2007: 143; Airoldi et al. 2014: 970; Kunnamo 2016: 69.)

In addition, it is revealed that value for the population can be achieved through the new and more feasible cross-boundary co-creation practices between healthcare and social sectors. With the tool it is possible to get a high amount of information and knowledge on population health, and possible to learn what kind of actions are needed, or not needed in a specific region or patient group. Common priorities and together ensured accessibility to the relevant health services and educated health professionals is valuable for the population, and the whole society. Further, other actors in the ecosystem such as peer support groups and related patient associations are considered to build value for the population health. It is also expected, in case it would be possible to reduce the bureaucracy and share more information between the sectors, that there are even more possibilities to develop completely new and value creating services for the population. Altogether, these above-mentioned value-creating factors, and the expected reduction in cost per capita of healthcare, generate value for the population health. (cf. Triple aim, Kinding & Isham 2014: 3).

5. CONCLUSIONS

In the latest era of digital disruption, new service platforms, advanced analytics and artificial intelligence are introduced in healthcare at increasingly fast pace. The potential benefits and value of advanced analytics of healthcare big data cannot be denied. The value promise presented in public discussion and proved in the research conducted so far, indicate the great potential that analytics have to improve the current value co-creation practices and generate better health outcomes for the individual patients as well as for the population health. The more versatile, larger, and higher-quality data resources that are used for the analytics, the more accurate results and better health outcomes can be achieved. The HBA tool uses, now, in the implementation phase structured patient data and evidence-based medical information for the analysis. The plan is to, in the future, increase the data volume, variety, and velocity, as well as number of algorithms and features of machine learning systems to predict the relative effects and duration of effects of the interventions. These developments provide further improved support for the health professionals in gaining even more accurate results based on the latest research and up-to-date data.

5.1. Key findings

The key findings of this study can be described with answering to the research questions and indicating the identified challenges and opportunities revealed during the research process. The answers are provided and discussed in the following paragraphs.

Indicated paths-to-value chains

The first research question on *how does big data and advanced analytics generate potential benefits and value for healthcare service providers, individual patients, and population health,* can be answered with the indicated paths-to-value chains, illustrated in Figure 10.

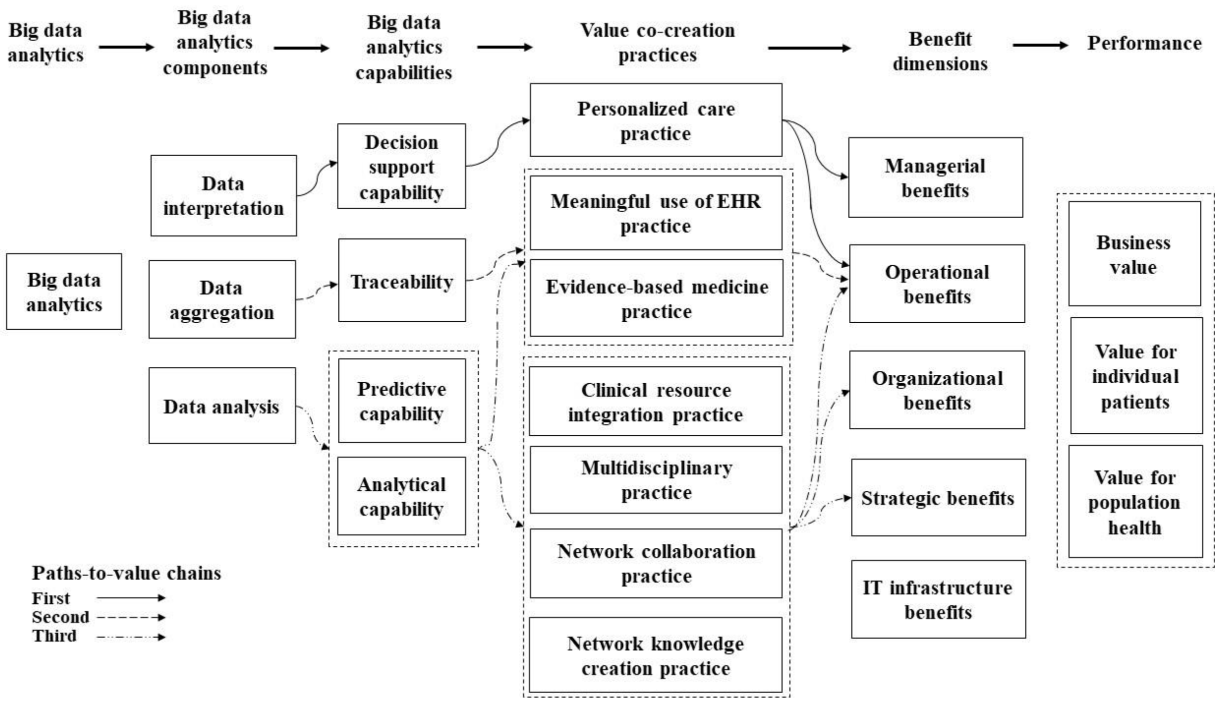

Figure 10. The most evident identified paths-to-value chains (illustration adapted from Wang et al. 2017: 10).

The first path-to-value chain describes how big data analytics, i.e. health benefit analysis generates value through the data interpretation component consisting of visual reports that support and enable better facilitation of mutual decision-making. That, in turn, affects personalized care practices by transforming it into a more interactive process between the doctor, other health professionals and the individual patient. This arises both operational and managerial benefits that further generate value for all stakeholders. Business value is generated for the healthcare service provider through improved quality, workflow efficiency, care planning and decision-making procedures that can lead to cost reduction and better performance. The business intelligence gained through health benefit analyses is also valuable for managing resource allocation and improvement of personnel management and employee satisfaction. Further, it can be claimed, that the better patient experience achieved by personalized care, generate business value, too. This path-to-value chain provides value for the individual patient by offering the possibility to become an active actor in his/her own healthcare. The possibility to influence one's own care by choosing between interventions and participating in shared decision-making to greater extent than before, can be claimed to lead to better patient experience. Value for the population health is generated when the operational and managerial benefits gained through the health benefit analysis reports support to target treatments to those who benefit the most from them, which consequently leads to reduced health inequalities.

The second path-to-value chain of the health benefit analysis generates value for the stakeholders through data aggregation which refers to the versatile combination of data sources and algorithms enabling traceability of e.g. patients with a specific condition. Further, this makes more accurate evidence-based decision making possible and the use of EHR more meaningful as the patient data is not only stored, but also used for analysis purposes. The achieved benefits are mainly operational enabled by improved and accelerated use of information and data. The business value on this path is achieved mainly through improved productivity due to increased data utilization rates. The improved health outcomes enabled by more accurate clinical decisions can be claimed to generate value for the individual patients. On the population health level, the value of health benefits analysis arises from the possibility of conducting virtual health checks for the specific populations.

The third path-to-value chain is identified based on the analytical capability of the health benefit analysis, that is, depending on the viewpoint, advanced predictive analytics when it is used in evidence-based medicine to generate ranked lists on the recommended interventions and their possible health outcomes for the individual patients. Better predictive analytics, in form of individualized estimation of baseline risks, makes the quantitative estimation of value (net health benefit) more accurate. Moreover, optimized treatment choices on the individual level, value-maximizing and equal resource allocation on the population level, and patient-centered care on the care provider level are all promoted. (cf. Airoldi et al. 2014: 970; Kunnamo 2016: 69.)

Analytical capability can also be considered business intelligence when the results are used for the benefit of operational, organizational, and strategic functions. Benefits are achieved through the improvements in clinical resource integration and network collaboration and knowledge creation practices, as well as better coordinated multidisciplinary cooperation. The improvements in these activities in turn create value for the individual patients in form of evidence-based medicine practice and recommendations of interventions, as well as seamless patient experience. The level of the health benefit analysis' analytical capability provides business value and competitive advantage for the healthcare service providers as it acts as differentiator separating it from other service providers. Being able to present such value propositions to the patients, is also a source of business value.

Potential benefits

The empirical data verifies several operational, managerial, strategic, and organizational benefits generating value for the healthcare service provider. However, due to the nature of the HBA tool, most of the suggested IT infrastructure benefits are not realized. (cf. Shang & Sheddon 2002: 277; Wang et al. 2017: 3; Wang & Hajli 2017: 290, 293). Business value is prominent in strategic issues, such as in gaining competitive advantage through differentiation, support for additional innovations, and in contributing the shift into value-based healthcare (cf. Porter & Teisberg 2006:8; Cosgrove 2013), where the definitions of value is based on the betterment of the patient's health (cf. Rantala & Karjaluoto 2016: 34).

Value co-creation practices and healthcare ecosystem actors

Regarding the supportive research question, *how does big data and advanced analytics affect the value co-creation practices and actors in a healthcare ecosystem*, it can be stated that employing advanced analytics affects, to varying extent, the examined value co-creation practices identified in the literature (cf. Wang et al. 2017: 7; Frow et al. 2016: 31 – 33). The meaningful use of EHRs is affected mainly due to new requirements related to the structured patient data recording practices, and by providing possibilities to detecting specific trends and behavior related to population health, as well as conducting virtual health checks. Evidence-based medicine practices are affected as it is now possible to gain better real-time insights based on medical events and treatments regarding individual patient's health. Multidisciplinary cooperation and clinical resource allocation practices are enhanced with the insights generated from the health benefit analyses, which were not available before. Network collaboration and network knowledge creation practices are affected, because new cross-boundary cooperation modes are needed in order to build common understanding on patients, i.e. what is needed and how to prioritize. Finally, the personalized care practices are expected to be affected with a revolutionary transformation as the new value co-creation practice denotes business scope redefinition in the way how patients are now integrated as actors in their own healthcare practice (cf. Nordgren 2009: 121; Wang et al. 2017: 2 – 3, 7; Payne et al. 2008: 93 – 94).

The evolving co-creation practices set requirements for the healthcare ecosystem actors as well as they need to conform to new ways of working with patients and other actors that are professionals from other sectors and levels of the ecosystem (cf. Frow et al. 2016: 27). Moreover, new skills are needed related to structured recording of patient data and personalized care planning. In addition, there is a need for completely new competencies, especially regarding conducting health analytics and interpreting results, which can be fulfilled by, and training, completely new professionals, that are health analysts. It is also expected that new roles for doctors and other health professionals, such as hospitalists and care managers, are introduced.

Identified challenges

However, there are identified challenges to consider. There are for example ethical issues to address as the freedom to choose between interventions may lead to less effective choices in terms of health outcomes or costs. Sometimes it is even possible that patients are not mentally mature enough to take such decisions. There might also be some attitudinal challenges due to the changes in the value co-creation practices increasing the influence and decision power of the patients. Moreover, regarding privacy issues, the health professionals and service providers need to be cautious, in order not to breach any rules or regulations (cf. Delen 2014: 9). For example, the good intentions to practice preventive care with population level health benefit analyses, and proactively contacting patients who have been identified to be in need for specific interventions, can be troublesome from the privacy regulatory point of view. In some cases, this is not a problem and patients are mainly satisfied and happy that they are offered the needed care in good time. But when taking another view, where a health center is approaching citizens who are not already patients having an active customer relationship with the inviting health center, the invitation might be interpreted as breach of privacy.

Opportunities

There are yet many opportunities available to healthcare service providers using the HBA tool. They can develop even more new innovations and disrupting services in the field of healthcare. This, however, requires courage, and willingness to accept that there will be new professions and actors in the health ecosystem. There are opportunities for professional development as information technology and analytical skills are increasingly needed to meet the requirements set by preventive care practices and the demand for health coaching services among health service consumers and patients. Opportunities for innovation and development are created also for the educators of health professionals, as they are in key position when transferring the knowledge, practices and working culture to the future health professionals.

Since knowledge regarding health issues is increasing among population, and as it is evident that people have access to constantly developing analytical tools, they have the opportunity to make better choices regarding their lifestyle. Further, the transfer into more personalized care practices in the healthcare services provides the opportunity to patients to be in a central role in the value co-creation of their own health outcome. Due to this and the fact that the value co-creation practices become increasingly data-driven, it can be claimed that the business scope redesign is on a disruptive and revolutionary level. (cf. Wang et al. 2017: 2 – 3, 7). In the population health management, the opportunity to identify the potential care gaps among population contribute to achieving reduced health inequalities (cf. Airoldi et al.2014: 970).

5.2. Theoretical implications

The theoretical implications of this study are manifold. First, the study contributes to filling the identified research gap regarding the business value of big data analytics in healthcare. This case study provides insight in how big data, i.e. structured patient data and evidence-based medical information, is used for advanced analytics purposes in Finnish healthcare setting.

The second theoretical implication arises from the need to extend the theoretical model which is used as a framework to examine the value for multiple stakeholders, that are healthcare service providers, individual patients, and population health. In practice, the big data analytics-enabled transformation model (Wang et al. 2017) which studies the big data analytics solely from the business value perspective, is complemented with viewpoints of value for individual patients and population health. These stakeholders are added to the study and theoretical model because it is important to understand also the individual patient's perspective in order to be able to develop the personalized patient centric care and motivate the patients to participate and acquire a more active role in their own care planning and shared decision-making. Regarding the population health perspective, it is essential to understand the generated value because it provides insights on how healthcare services should be targeted to close the indicated care gaps, which further supports the desired shift into value-based healthcare.

The third theoretical implication is to provide further understanding of the studied practices. The original theoretical model is concentrated on the examined practices from their IT-enablement perspective, while in this study they are examined from the value co-creation perspective.

With the stated modifications in the theoretical model, it is possible to examine the impacts of introducing health benefit analysis and the tool for conducting it and evaluate the desired value for respective stakeholders. When conducting a study on big data analytics, it is also essential to understand the distinction between the characteristics of business intelligence, advanced analytics, artificial intelligence and beyond.

This study also reveals the theoretical implications regarding the need to revise the traditional views on actors in value co-creation. This is due to the fact that in addition to the human actors in value co-creation, also new digital actors, such as algorithms are becoming an essential part of the healthcare ecosystem. Introducing the data-driven practices in value creation and ecosystems is a disruptive change, which can be even considered to cause a paradigm shift (cf. Groves et al. 2013: 7; Lusch et al. 2016: 2960; Rantala & Karjaluoto 2016: 40).

5.3. Managerial implications

Managerial implications of this study raise firstly the importance and criticality of the commitment and support from management when introducing big data analytics as suggested in theory (cf. Delen 2014: 240 – 241) and as revealed in the analysis of the empirical data of this study. The management needs to ensure that the efforts are aligned with the business strategy and information technology environment and that the quality of data supports the implementation advanced analytics. Moreover, management needs to allocate enough resources, such as budget, time, and professionals like project manager, developers, subject matter experts, and other project workers in the project. As this project is carried out in healthcare, it is important to involve health professionals' in the development and give weight to their views because for example nurses, doctors and other health specialists can provide valuable input to the development of the tools and related processes. In addition, data privacy, security, governance, and ethical aspects are managerial challenges which need to be considered when implementing advanced analytics in the field of healthcare (cf. Sivarajah et. al 2017: 265).

Management needs also to consider that when a new tool that impacts and changes the status quo on many levels in the health ecosystem is introduced, it is important that it is properly integrated to the processes and that it becomes a natural part of the systematic way of working. It should also be remembered that the new analytical tool is not working by itself, but it needs management's attention to ensure that also the health professionals commit to using it. It also needs to be ensured that the overall health service design supports the evolved value co-creation practices, especially regarding the personalized care practice and visualization of the reports so that the results can be interpreted without misunderstandings.

It can also be concluded that there is an evident need to clarify and raise awareness of the HBA tool's value promise for communication to the public (cf. European Union 2016: 55), as well as for commercialization to the domestic and international markets. In addition to the benefits and proposed value to the stakeholders, the level of current analytical capabilities and changes and requirements regarding the value co-creation practices should be explained to the desired target audiences.

5.4. Suggestions for future research

As this study concentrates on the expected benefits and impacts in value co-creation practices from the developers' and pilot users' point of view, it would be of interest to conduct a follow-up study after a while to learn how the benefits and effects on value co-creation practices have been realized. Likewise, it would be of interest to learn how the requirements due to employing advanced analytics has impacted the healthcare ecosystem actors, their relationships and work culture, as well as how the change management in such major shift could be facilitated. Moreover, it would be interesting to study how the actors have adapted to the affected or new value co-creation practices, for example what went well and what was challenging.

To study more especially strategic benefits and business value achieved through advanced analytics would also be of interest. In addition, studies on patients' experiences of personalized care and using health benefit analysis, as well as becoming an active actor in value co-creation, would be interesting. Likewise, the actual impacts in the population health and expected reduction in health inequalities are of interest.

Similar studies in international context would be interesting, too. For example, covering selected EU countries, or other geographical areas to compare the maturity of digitalization and preparedness for applying advanced analytics in healthcare in various countries.

5.5. Limitations

The HBA development project is in the time of conducting this study in a pilot phase. Therefore, the realization of the anticipated impacts in value co-creation practices and potential benefits are recommended to be revised after the HBA tool has been in active use for several months. Since this study examines the implementation of the HBA tool in Finland in specific health centers at a certain point of time, the results are limited to describing only the current situation in these health centers. The empirical results of this study may, however, guide other Finnish or international healthcare service providers who intend to introduce the HBA tool.

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APPENDIX 1. Examples of results generated with Health Benefit Analysis tool

The following examples illustrate the results of Health Benefit Analyses for an individual patient as a list of net impacts of different interventions (Table 1), health impact of Ivabradin (drug) for the same individual patient (Table 2), and an example of health benefit on population level (Table 3).

Example 1.

The health benefit analysis for an individual is a tool for making a care plan. Estimating net benefits or harms of interventions by allowing the person to determine the importance of each outcome could help in shared decision-making when making choices between alternative interventions.

Intervention	Condition	Potential to benefit
Sacubitril	Heart failure	15.58
Ivabradine	Heart failure	14.80
Colorectal cancer screening	N/A	0.90
PSA screening	N/A	-5.64

Table 1. Health benefit analysis for an individual.

The health benefit analysis is listing interventions that the person has not yet received, and their estimated health impacts. In this example, also an intervention with marginal net benefit (colorectal cancer screening) and one with net harm (PSA screening) are shown.

Example 2.

The health impact (benefit or harm) of a single outcome of an intervention is calculated by multiplying the absolute effect with the importance of the outcome. The net benefit or harm of an intervention is the sum of net impact of all its outcomes.

Outcome	Relative effect	Baseline risk	Absolute effect	Number needed to treat (NNT)	Severity of outcome	Duration of effect	Importance of outcome	Benefit or harm
Death from any cause	0,1765	0,17	0,030	33,3	10	60	600	18,0
Hospitalization for heart failure	0,222	0,225	0,050	20,0	8	1	8	0,40
Symptomatic bradycardia	-4,0	0,01	-0,04	-25.0	2	15	30	-1,20
Visual adverse effects	-2.0	0,01	-0,020	-50,0	2	15	30	-0,6
Atrial fibrillation	-0,125	0,08	-0,010	-100,0	3	60	180	-1,80
Health impact								**14,8**

Table 2. Health impact of Ivabradine (drug) for heart failure.

Calculating the health impact of an intervention on the basis of knowledge (green), importance of each outcome as determined by the individual (red), and numbers calculated from these numbers (yellow). The baseline risk should be estimated individually. The following calculations are performed in the table: Absolute effect = relative effect x baseline risk. NNT (number needed to treat) = 1/absolute effect. Importance of outcome = severity of the outcome x duration of the outcome (expressed in months – the maximum time span in the example is 5 years = 60 months). Benefit or harm = absolute effect x importance of outcome. Health impact = sum of all values in the benefit or harm column (benefits are expressed as positive values, harms as negative values).

Example 3.

On the population level, the health benefit analysis helps in allocating resources for the provision of interventions that result in the largest health benefit for the population. If data on the unit costs of interventions are available, the interventions can be ordered according to cost-effectiveness by using net benefit as a measure of effectiveness.

Intervention	PTB average in the population	Cost of the intervention for one patient	Cost/PTB (cost effectiveness)	Number of patients in need of intervention (N)	Health benefit in the population (PTB x N)	Cost of treating all patients (Cost x N)
Smoking cessation counseling	0.27	500	1851	3000	810	1 500 000
Statin	0.49	1000	2040	1800	882	1 800 000
Arthroplasty (knee osteoarthritis)	2.4	20 000	8333	200	480	4 000 000

Table 3. Potential to benefit from various interventions in the population.

An example of health benefit from filling the care gap in a population for three interventions in example case of managing a health care budget and have limited resources. Results of health benefit analysis provide support with deciding which programs to support: smoking cessation counseling for all eligible, statins for all eligible, or total knee arthroplasty for all eligible.

(Examples adapted from Kunnamo 2016: 67; Kunnamo & Alper 2016; 18, 22 – 23; Kunnamo & Alper 2017: 1 – 4).

APPENDIX 2. Step by step description of health benefit analysis

1. All data about the patient (from the EHR (electronic health record), PHR (personal health record), wearable devices, Kanta eArchive, biobanks) is the starting point in making a care plan.
2. Clinical decision support based on trustworthy guidelines analyzes the data by using evidence-based rules, risk calculators and databases (including big data and genomic databases). A PICO (Patient group, Intervention, Comparator, Outcome) ontology links evidence to the health problems and characteristics of the individual patient.
3. Clinical decision support identifies care gaps and interventions that could improve health outcomes of the patient.
4. Recommendations are constructed to fill the care gap. If the patient has many health problems, individual recommendations from many clinical practice guidelines and care pathways will be listed.
5. Clinical decision support tools that utilize risk calculators, prognostic models, and interactive summary of findings tables of research evidence are used to quantify benefits and harms individually for the patient, so that the interventions that would benefit the patient most are on top. Interactions of interventions (such as drug-drug interactions), and concordant and discordant recommendations are taken into account at this stage.
6. The recommendations are shown to the patient, using decision aids that make the benefits, harms, and burdens of interventions easier to understand. The patient chooses which interventions he or she is willing to use. The patient defines his or her individual targets (together with the professional) according to the principles of the chronic care model.
7. The interventions that have been chosen to be performed are recorded in the structured care plan. Care protocol templates can be used for recording bundles of interventions.
8. The actions recorded in the care plan have codes that can be analyzed to guide the process of care and the provision of care for the whole population.
9. The patients are offered self-care interventions and tools and on-line health coaching.
10. Actions needed from health care professionals serve as input to resource planning tools that link the actions with the competencies, equipment, rooms, and other resources needed for their completion. Bookings can be automated and can also be made by the patient.
11. The resource planning tools place the actions on the task list and schedule of professionals. Tools are provided that make the work easier and faster. The right thing is made the easy thing to do.

12. The resource planning tools have access to all care plans of all people in the population. In this way the volume of care needed, and the availability of resources is known when the care plans are made for individual patients. If overuse of resources threatens, the care plan can be modified. When prioritizing actions for individual patients in the population, the conclusions from steps 5 and 6 are used as guidance.
13. The patient and the professional meet face-to-face or virtually.
14. The professionals record observations and interventions in the structured EHR from where they are forwarded to the national eArchive and big data repository.
15. The patient records his or her health data, symptoms, and functional ability, as well as measurements from home monitoring into the PHR from where they are available for analysis by CDS.
16. The data recorded by the professionals, patients, and devices are anonymized and stored in a big data repository where they are used for the creation of new knowledge and for developing prediction models. The big data repository can also receive data from the patient's environment, and position data can be linked with patients.
17. CDS uses both individual patient data and big data for determining the patient's baseline risk for events, and making recommendations ("search from history earlier patients that are similar to the index patient and see what happened to them"). In a learning health care system every single data item (such as a single blood pressure measurement) contributes to knowledge. Similarly, every path of the patient can be analyzed for finding shortcuts in the care of future patients.

(Adapted form Kunnamo 2016: 65 – 66).

APPENDIX 3. Interview structure

Interviewee
Title
Company/Organization
Date/Duration

1. Describe the Health Benefit Analysis (HBA) tool development project and your organization's and your own role in it.
2. Why is the HBA tool developed and who are the main target groups?
3. Which competences or roles you expect are required in healthcare service delivery and ecosystem when the HBA tool is in use?
4. What kind of resources does the HBA tool consist of, such as databases and techniques?
5. What kind of data and information types the tool uses?
6. Describe the capabilities of the tool, e.g. in terms of traceability, analytical capability, decision support and predictability. What additional features or capabilities you would think would be useful in the tool?
7. How does the use of the HBA tool enhance or change the following practices or way of working in healthcare service delivery?
   - Meaningful use of electronic health records practices
   - Evidence-based medicine practices
   - Practices in multidisciplinary teams
   - Clinical resource integration and allocation practices
   - Network collaboration practices
   - Network knowledge creation practices
   - Personalized care practices
   - Other healthcare service delivery practices
8. How would you describe the benefits of using the HBA tool for healthcare service providers through the following benefit dimensions?
   - IT infrastructure benefits
   - Operational benefits
   - Organizational benefits
   - Managerial benefits
   - Strategic benefits

9. In your opinion, what are the benefits of using the HBA tool for individual patients? What does it require from the patients themselves?
10. In your opinion, what are the benefits of using the HBA tool for the population, living e.g. in the area of a specific health center?
11. Do you see any specific challenges or barriers regarding the development or usage of the HBA tool?
12. What makes the development and usage of the HBA tool possible?
13. Do you have anything else in mind regarding the development or usage of the HBA tool?
14. In your opinion, what is most important to consider in the HBA tool development and implementation?