Applied data science in patient-centric healthcare: Adaptive analytic systems for empowering physicians and patients

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ABSTRACT

We define the emerging research field of applied data science as the knowledge discovery process in which analytic systems are designed and evaluated to improve the daily practices of domain experts. We investigate adaptive analytic systems as a novel research perspective of the three intertwining aspects within the knowledge discovery process in healthcare: domain and data understanding for physician- and patient-centric healthcare, data preprocessing and modelling using natural language processing and (big) data analytic techniques, and model evaluation and knowledge deployment through information infrastructures. We align these knowledge discovery aspects with the design science research steps of problem investigation, treatment design, and treatment validation, respectively. We note that the adaptive component in healthcare system prototypes may translate to data-driven personalisation aspects including personalised medicine. We explore how applied data science for patient-centric healthcare can thus empower physicians and patients to more effectively and efficiently improve healthcare. We propose meta-algorithmic modelling as a solution-oriented design science research framework in alignment with the knowledge discovery process to address the three key dilemmas in the emerging "post-algorithmic era" of data science: depth versus breadth, selection versus configuration, and accuracy versus transparency.

1. Introduction: applied data science in patient-centric healthcare

In this position paper we argue how applied data science for patient-centric healthcare can empower physicians and patients to more effectively and efficiently improve healthcare. We propose a solution-oriented research framework to address the three key dilemmas in the emerging *"post-algorithmic era"* of data science as identified by Spruit and Jagesar (2016). First, the *depth* versus *breadth* dilemma focuses on the necessity to overcome the heavy mathematical terminology in data science literature as an adoption barrier for non-computer scientists. Second, the *selection* versus *configuration* dilemma revolves around the observation that many users leave the algorithmic (hyper-)parameters to their default settings and base algorithm selection substantially on reputation or intuitive appeal (Thornton et al., 2013), which often results in underperforming algorithms and suboptimal results. Third, and finally, *accuracy* versus *transparency* concerns the trade-off between optimal performance through *"black box"* techniques such as deep neural networks and maximally interpretable algorithm outcomes such as association rules.

But let's first take a few steps back from the state-of-the-art machine learning challenges outlined above. At its essence, the novel research fields of data science and big data analytics focus on how to learn directly from data itself, so that we can, for example, describe our personal state of well-being over time based on the sensor data from our smartwatch, or predict what customers are likely to buy next based on their previous purchases and webshop behavior, or even prescribe what the best decision is based on all recorded experiences. As long as there is enough high-quality annotated data available, recent developments indicate that nearly anything is possible: from automatically identifying people on video, and generating textual descriptions for images, to optimising buy-or-sell decisions in high-frequency trading and prescribing personalised medications to patients… Data science is swiftly changing and increasingly reshaping our interactions with the world around us.
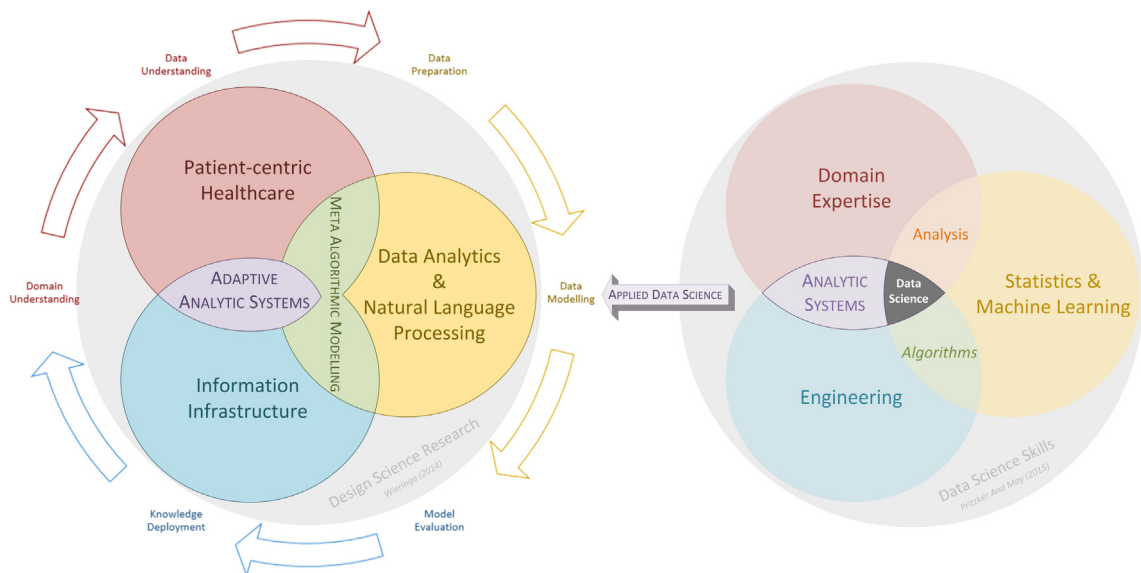
Fig. 1. Research framework for applied data science in patient-centric healthcare.

1.1. Applied data science

1.1.1. Science

But… what exactly is data science? To explain that, let's first briefly discuss science itself, as shown in the data science skills diagram in Fig. 1. Suppose that a researcher wants to investigate a new problem statement. First, he applies his domain expertise to formulate a relevant research question (shown in red in Fig. 1). Second, he formulates a study design and selects the most appropriate statistical methods (shown in yellow in Fig. 1). Third and finally, he collects the data and analyses them as specified beforehand in the research design (shown in orange), hopefully finding an answer to his research question. In a nutshell, this is the ubiquitous scientific method in action.

1.1.2. Data science

However, in data science, one more dimension is added to the mix: engineering. Engineering (in blue in Fig. 1) refers to technologies and architectures that actually implement the data analysis. This often requires some programming. Because data scientists "build stuff", to see if it actually works in daily practice as theorised. Furthermore, machine learning techniques are used to complement statistics (shown in yellow in Fig. 1). This is in line with Pritzker and May's (2015) definition of data science as *"the extraction of actionable knowledge directly from data through a process of discovery, or hypothesis formulation and hypothesis testing"*. Blei and Smyth (2017) similarly argue that the three-dimensional perspective upon data science as a research field in its own right—which they refer to as holistic data science—necessarily consists of statistical, computational, and human components. We note that these three critical components directly map to Pritzker and May's Venn-diagramme areas of statistics & machine learning, engineering, and domain expertise.

On a final note related to Fig. 1, we are particularly interested in the "Analytic Systems" overlap (shown in purple in Fig. 1) between the domain expertise and engineering skills. Because, when data science research focuses on the "Analytic Systems" aspects in particular, implying advanced software engineering efforts, we can define this research field of study as Applied Data Science (ADS) in line with Spruit and Jagesar (2016):

"Applied Data Science (ADS) is the knowledge discovery process in which analytic systems are designed and evaluated to improve the daily practices of domain experts".

1.1.3. Applied data science

In applied data science the primary aim is to improve the real world around us, directly, in search for maximum societal impact. As the use of big data becomes more prevalent within the fields of Healthcare, Security, Business, Education and Social Networks, researchers have begun to examine how data from these environments can be better stored, analysed, and mined. Note that, in contrast to fundamental data science, applied data science research primarily focuses on applying machine learning techniques to solve stringent issues in daily practices of domain experts, by developing advanced software systems that provide an effective and efficient end-user environment to embed the machine learning or statistical techniques into. In other words, in applied data science it is not a primary objective to develop novel statistical and machine learning techniques for doing data science in a better way. However, if applying existent machine learning techniques do not suffice, then this will trigger more theoretical data science research

to develop the necessary techniques that do solve the problem at hand.

Furthermore, we observe a particular rise in attention to such advanced software systems in the Healthcare, Security, Business, Education and Social Networks domains. These technologies aim to improve the quality of work in the daily practices of physicians, patients, businessmen, and educators. Advanced systems for applied data science may also reduce clinical risks, financial crises, and educational failures. At the same time, physicians, patients, businessmen, and learners will be part of the process, having more information delivered to their devices instantly. They will have more information to deliver a better service and dynamic guidelines to improve their quality of life in every aspect and reduce risks. In other words, applied data science can provide physicians, patients, businessmen and educators empowerment, increasing, in turn, motivation to use and, subsequently, data creation. These data can, in turn, be used in management systems for KPI (Key Performance Indicator) delivery, among others.

Finally, we also include patient-centric *business intelligence* and *data analytics systems* in healthcare within our applied data science context as specified above and in Fig. 1, adhering to well-established definitions. First, we consider *Business Intelligence (BI)* as an umbrella term that combines architectures, tools, databases, analytical tools, applications, and methodologies. Business intelligence's major objective is to enable easy access to data and models to provide business managers with the ability to conduct analysis (Turban et al., 2013). Business intelligence systems, therefore, combine data gathering, data storage, and knowledge management with analytical tools to present complex internal and competitive information to planners and decision makers (Negash, 2004). Second, *Data Analytics (DA)*, or data mining, is the nontrivial process of identifying valid, novel, potentially useful, and ultimately understandable patterns in data stored in structured databases (Fayyad et al., 1996a). Data analytics is considered to be one of its four key architectural business intelligence functions, next to data-warehousing, business performance management, and user interfacing. Third and finally, One particular data analytics technique has become increasingly more central to knowledge discovery processes in patient-centric healthcare in recent years: *Natural Language Processing (NLP)*. Natural language processing, or text analytics or text mining, is a subfield of linguistics and computer science that deals with computer applications whose input is natural language (Gandomi and Haider, 2015). Natural language processing can be pursued from both a symbolic/rule-based or statistical/probabilistic approach to automatically derive or learn lexical and structural preferences from corpora (Manning and Schütze, 2001), by employing computational techniques for the purpose of learning, understanding, and producing human language content (Hirschberg and Manning, 2015).

1.2. Patient-centric healthcare

The adoption of advanced healthcare information systems and telematics applications in healthcare requires an integrated approach to social, economic, political and cultural impacts and challenges of information and communication technologies. Smart data, and data analytics along with cognitive computing, are promising technologies with great interest for the healthcare domain. Therefore, we focus on analysing these social, economic, political and cultural impacts and challenges on the impact of patient-centric business intelligence and data analytic systems in healthcare, which we collectively consider from an applied data science perspective. It is our hope that this special issue may serve as a communication vehicle for the promotion of a holistic—*i.e.* beyond the technical—approach to the evolution of patient-centric healthcare systems incorporating social, political, economic and cultural factors.

Healthcare is known to be a complex system, in which the nonlinear interactions between its people, process, and technology components determine its success (Lipsitz, 2012). Many stakeholders and medical processes are heavily intertwined within a single person's healthcare ecosystem, ranging from the primary care's general practitioner's office up to secondary care's specialists and even academic medical centers (Green et al., 2001). Due to compliance regulations and ecosystem interdependencies, the healthcare sector has proven to be a particularly challenging though potentially rewarding sector to introduce business intelligence systems successfully. It is noteworthy to mention that studying the domain of healthcare through a *complex adaptive systems (CAS)* lens can be considered as a standardised research framework to uniformly investigate knowledge discovery processes across disciplines. Example domains range from diverse disciplines such as fisheries (Mahon et al., 2008), organisations (Boisot and Child, 1999), to even language (Beckner et al., 2009). Central to complex adaptive systems is that they involve many components that adapt or learn as they interact (Holland, 2006), which are rather similar to the people-process-technology interdependencies at the heart of information systems research (Khodabandeh and Palazzi, 1995).

The question, then, is how to measure the impact or success of a healthcare artifact's design or implementation as an intervention instrument. It may be assessed under laboratory conditions within a clinical trial context, or as a value-adding tool in daily practice of healthcare professionals, among others. Then, possible metrics include efficacy, effectiveness, efficiency, satisfaction (or: usability), perception, intent, and usefulness scores (*e.g.* Croll, 2009). However, measuring efficacy in clinical studies is both very expensive and resource-intensive. Effectiveness in daily practice suffers from the same restrictions, as physicians are known to have extremely limited time to participate in improvement studies, and patients may be equally hesitant as they may not benefit directly themselves from the study. Efficiency and usability measurements often require production-ready systems to be in place for proper evaluation, which often take years to develop. It is no wonder, then, that costs for healthcare have been steadily growing throughout the last decades (Spruit et al., 2014).

One possible solution to the ever-rising costs and optimization of the quality of care, has been to pursue a patient-centred approach. Patient-centredness is regarded as crucial for the delivery of high quality care by doctors, but more research is needed to measure the impact of processes and outcomes of patient-centred care (Mead and Bower, 2000). Therefore, we aim to gauge the current state-of-the-art in circumventing barriers to data analytics and business intelligence success in healthcare by focusing on patient-centric systems to better realise the potential applied data science impact. We want to explore how to design, co-create,

develop and evaluate patient-centric applied data science systems for healthcare that showcase its potential societal impact.

2. Methods: design science research for knowledge discovery

For our applied data science approach we propose a novel research design that integrates two proven approaches to combine scientific research rigour with societal impact in daily practices, as shown in Fig. 1: the Knowledge Discovery Process (Chapman et al., 2000) and the Design Science Research framework (Hevner et al., 2004). Applied data science as a dual research approach aims to bridge the research traditions of *Applied Research* and *Theoretical Research*, respectively, through a unified *Application-oriented, or Solution-oriented, Research* approach. We discuss the two approaches below.

2.1. Knowledge discovery process

The Knowledge Discovery Process (KDP), akin to Knowledge Discovery in Databases (KDD), "creates the context for developing the tools needed to control the flood of data facing organizations that depend on ever-growing databases of business, manufacturing, scientific, and personal information" (Fayyad et al., 1996b). Even though many process models have been developed, the CRoss-Industry Standard Process for Data Mining (CRISP-DM) is widely considered to be the Nr. 1 knowledge discovery process guideline in the data science industry to perform Applied Research based on 20 years of best practices (Shearer, 2000; Kurgan and Musilek, 2006; Mariscal et al., 2010). In this context applied research denotes that the process outcomes aim to contribute new knowledge to the application domain under investigation, such as healthcare. At the conceptual level CRISP-DM consists of six cyclic phases as shown in Fig. 1, which we compress into three intertwining aspects within the knowledge discovery process: domain and data understanding, data preprocessing and modelling using natural language processing and (big) data analytics techniques, and model evaluation and knowledge deployment through information infrastructures.

First, the domain and data understanding (*i.e.* problem investigation) phase requires modelling of the application domain, including hypothesis generation, and exploratory data analysis to understand the often unstructured or semi-structured data. We provide three examples. First, Spruit et al., (2014) uncover the potential for data-driven long-term care. Second, Syed et al. (2018) capture the complexity of the fisheries domain through a latent topic analysis of most journal articles in the domain from 1990 to 2016. Third, Baars et al. (2016) develop a custom survey instrument to understand and quantify the influence of organisational characteristics within the information security domain through an adaptive maturity model for incremental process improvement.

Second, in the data preprocessing and modelling (*i.e.* treatment design) phase the data need to be semantically processed before they can model potential insights to help answer the raised hypotheses. This requires hypothesis-sensitive Natural Language Processing (NLP) techniques, where we focus on technique selection and configuration for decision making in daily practices. We provide three examples. First, in Spruit and Vlug (2015) we present a text snippet enrichment process for automatic classification of financial transactions. Second, Menger et al. (this issue) develop an information extraction method for automatic de-identification of Dutch medical texts. Third, in Syed and Spruit (2017) we examine the quality of latent topics in scientific publications when employing Latent Dirichlet Allocation (LDA) topic analyses based on either abstract or full-text data as a configurable hyperparameter.

Third and finally, once the analytic model performs well in controlled computational experiments, the model evaluation and knowledge deployment (*i.e.* treatment validation) phase shifts to software prototype engineering to create an adaptive analytic system with which one can determine the system's utility determinants in daily practice. For example, Meulendijk et al. (2015b) evaluate their STRIPA analytic system's usability for physicians to optimise medical records for polypharmacy patients by jointly measuring its effectiveness, efficiency and user satisfaction. It is in this knowledge deployment step that this research theme particularly aims to contribute to the body of knowledge on *Information Infrastructures*, which in its broadest sense, is *"the technical, social, and political framework that encompasses the people, technology, tools, and services used to facilitate the distributed, collaborative use of content over time and distance"* (Borgman, 2010:19). An information infrastructure can refer to either a schema-on-write datawarehouse, a schema-on-read big data lake or a distributed Apache Spark-based computing cloud, which is (to be) used in daily practices. We consider dilemmas such as interoperability versus uniformity, data quality versus usability, and standardisation versus situationality (*e.g.* Hanseth et al., 1996). We provide three examples. First, van Dijk et al. (2017) describe a data quality resolving architecture in the justice domain. Second, Shen et al., (2016) present a federated information architecture for the medication review process in multinational clinical trials. Third, Tawfik and Spruit (2018) demonstrate the SNPCurator analytic system for enriched, interactive literature mining of SNP-disease associations.

2.2. Design science research

In contrast, the Design Science Research (DSR) paradigm *"seeks to extend the boundaries of human and organizational capabilities by creating new and innovative artifacts"* (Hevner et al., 2004). This type of research is primarily solution-oriented (*i.e.* application-oriented), in contrast to being either mostly applied or theoretical. Brocke et al. (2017) more recently formulate its aim as *"developing purposeful IT artifacts and knowledge about the design of IT artifacts"*. Peffers et al. (2007) notably describes the DSR process as a methodological set of activities ultimately leading to the creation of the design artifact, including the identification of problem, definition of objectives, design & development, demonstration, and evaluation.

Wieringa (2014) explains the distinction between design problems and knowledge questions in design science research. Whereas design problems are treated by following the design cycle, knowledge questions are answered by following the empirical cycle. Wieringa's (2014) design cycle for performing design science research from a problem-solving perspective consists of an iteration

over the following three main steps: problem investigation, treatment design, and treatment validation. However, in applied data science we investigate knowledge questions by employing the knowledge discovery process, preferably CRISP-DM, being the undisputed standard in this research area. Therefore, we align Wieringa's design science cycle and CRISP-DM's knowledge discovery process by linking problem investigation to domain understanding and data understanding, treatment design to data preparation and data modelling, and treatment validation to model evaluation and knowledge deployment.

From this methodological viewpoint, then, an analytic system prototype functions as a research intervention instrument. Such a prototype is used to evaluate the design science artifact under development (*e.g.* a method, model, process, framework, or architecture), employing metrics such as effectiveness, efficiency and usability to determine the analytic system's societal impact. We refer to Prat et al. (2014) for a rather complete overview of relevant artifact evaluation metrics.

3. Theory building: meta-algorithmic modelling

To ensure scientific rigour, enable standardisation and develop theory, a research and development process of a design science artifact should be performed according to an expert-reviewed and approved methodolody. Methodology literally means a *"science of methods"* and thus provides a consistent framework for methods that specify how to properly execute projects. A method may, in turn, incorporate various techniques that specify and facilitate specific steps within a project.

3.1. Meta algorithmic modelling

For applied data science research in combination with knowledge discovery processes, we here propose *Meta-Algorithmic Modelling (MAM)* which Spruit and Jagesar (2016) define as *"an engineering discipline where sequences of algorithm selection and configuration activities are specified deterministically for performing analytical tasks based on problem-specific data input characteristics and process preferences"* as an appropriate method. We argue that this design science research dimension effectively extends the reusability and generalisability of the industry-standard CRISP-DM knowledge discovery process (*e.g.* Lefebvre et al., 2015), thus contributing to the scientific body of knowledge by providing proven recipes for properly addressing the three key data science dilemmas given a problem-specific challenge.

Spruit and Jagesar (2016) note that MAM as a discipline is inspired by Method Engineering, "the engineering discipline to design, construct and adapt methods, techniques and tools for the development of information systems" (Brinkkemper, 1996). In related work, Simske (2013) describes a reusable, broadly-applicable set of design patterns to empower intelligent system architects. Finally, MAM also conceptually resembles the Theory of Inventive Problem Solving (TRIZ), a method for creative design thinking and real problem solving, partly due to its "Meta-Algorithm of Invention" (Orloff, 2016). Analogous to the meticulous definitions of Wynekoop and Russo (1995), we can also reformulate our Meta-Algorithmic Modelling methodology as follows:

> "Meta-Algorithmic Modelling (MAM) is the systematic approach to facilitate conducting at least one complete knowledge discovery process phase consisting of a set of guidelines, activities, techniques and tools, based on a domain-driven philosophy of data analysis, which contains analytic techniques in specific steps for conducting at least a portion of a phase within the knowledge discovery process, and which visually represents the sequence of analytic steps to perform within the knowledge discovery process, to enable theory building within the applied data science domain".

As Spruit and Jagesar (2016) note, the strategic goal of MAM is to provide highly understandable and deterministic method fragments to guide application domain experts without in-depth machine learning (ML) expertise step-by-step through an optimized ML process following Vleugel et al., (2010) and Pachidi and Spruit (2015), among others, based on the Design Science Research approach. We thereby promote reuse of state-of-the-art ML knowledge and best practices in the appropriate application of ML techniques, whilst at the same time provide information on how to cope with challenges like parameter optimisation and model transparency (Pachidi et al., 2014).

3.2. Adaptive analytic systems

We conceive *Adaptive Analytic Systems (AAS)* as an engineering approach to investigate intertwining aspects of the three dual phases of the knowledge discovery process with a solution-oriented design science research approach within an applied data science context. Following the Applied Data Science definition above, this indicates that we *"design and evaluate analytical systems to improve the daily practices of domain experts"*, in contrast to more theoretical data science which primarily aims to develop novel statistical and machine learning techniques for improving data science itself. Nevertheless, novel applications of data science methodology and engineering in a particular scientific domain likely result in new theoretical data science research questions, in line with the UPADS (2017) Starting Document, among others. We are particularly interested in Meta-algorithmic modelling solutions with respect to the three key dilemmas in data science as outlined in the introduction above: depth vs breadth, selection vs configuration, and accuracy vs transparency.

3.2.1. Analytic system

We construct our definition of an analytic system from existing definitions of *Analytics* and *Computer-Based Information systems* as well-established foundations. Firstly, Kiron and Shockley (2011) define analytics as *"the use of data and related insights developed through applied analytics disciplines to drive fact-based planning, decisions, execution, management, measurement, and learning"*. Secondly,

Stair and Reynolds (2017) define a computer-based information system (CBIS) as *"a single set of hardware, software, databases, networks, people and procedures that are configured to collect, manipulate, store and process data into information"*. We, therefore, define an Analytic System as follows:

> "An analytic system is a specialised information system for performing analytical tasks based on problem-specific data input characteristics and process preferences".

> Interestingly, Stair and Reynolds' (2017) definition of a CBIS *procedure* is *"a set of steps that need to be followed to achieve a specific end result"*. The analytic system modelling definition above can in this context also be understood as an elaboration of an "analytic procedure": a communicative recipe for performing analytical tasks by domain experts.

3.2.2. Adaptive analytic system

The *Adaptive* component in our applied data science research prototypes relate to their attention to data-driven personalisation aspects within such systems. In the domain of healthcare, this includes *precision medicine* and *personalised medicine* (PM), which aim to contribute to more patient-centric and patient-tailored detection, prevention and treatment of diseases (*e.g.* Agyeman and Ofori-Asenso, 2015). A recent biomedical example is the SNPcurator which automatically extracts single-nucleotide polymorphism (SNP) associations of any given disease and its reported statistical significance (*P*-value) and odd ratio as well as cohort information such as size and ethnicity. It includes user interaction features such as search query customisations, results sorting, and information expansion on demand as personalisation features (Tawfik and Spruit, 2018). A mature healthcare analytic system is the STRIP Assistant platform for prescriptive analytics (Meulendijk et al., 2015a; Shen et al., 2016), a Clinical Decision Support System (CDSS) that assists physicians to optimise medical records for polypharmacy patients by measuring utility determinants such as the adaptive analytic system's effectiveness, efficiency and user satisfaction (Meulendijk et al., 2015b; Meulendijk et al., 2016). Each medication advice can either be accepted or ignored by the prescribing physician and influences and personalises all subsequent advices. These individual and personalised decisions can be interpreted as labeled data annotations to supervise machine learning algorithms (Meulendijk et al., 2017).

Furthermore, recent years also marked a rise in the development of (semi-)automated initiatives related to data identification, feature engineering, model selection and analysis, even creation of natural language narratives for the results. Prototypes such as *The Automatic Statistician* and *The Data Science Machine* merely require raw data as input in order to turn it into information by means of appropriate statistical analysis. Their outputs can vary from identification of interesting correlations within the dataset to automatically generation of natural-language articles presenting the information as a narrative (Tarran and Ghahramani, 2015; Kanter and Veeramachaneni, 2015). The arrival of such tools, which we classify as *Automatic Adaptive Analytic Systems*, will no doubt further propel the societal impact of applied data science as a research discipline.

4. Results: papers in this special issue

In this special issue of *Telematics and Informatics* we provide a state-of-the-art overview of the emerging research domain of applied data science in healthcare, which primarily aims to improve the daily routines of physicians and patients by performing an iterative knowledge discovery process and to guide the agile development of an embedded analytic system. We briefly introduce each contribution to this issue, grouped by their key contribution to the patient-centric healthcare knowledge discovery process, as visualised in Fig. 2.
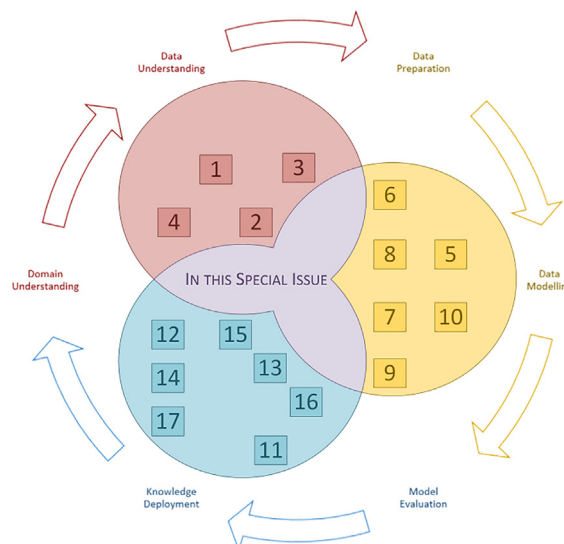

Fig. 2. The papers in this Special Issue positioned in the Applied Data Science research framework.

4.1. Problem investigation: domain and data understanding

[1] Papanastasiou et al. (2017) present a literature review that explores patient-centric ICTs as a new paradigm in healthcare assessment and intervention practices for students with learning, physical or sensory disabilities. Their results show the impact of the interoperability of healthcare information between patients' healthcare records and information systems which facilitate healthcare systems to be lifesaving if available at the time of medical examination, among others.

[2] Zheng et al. (2017) perform a systematic review to provide an overall understanding of how academic research can be incorporated into business intelligence solutions to ensure patient-centredness. Analysing the period 2000–2016, results indicate that the number of business intelligence applications that include patient-centredness have continued to grow since 2010, and that they primarily focus on the dimensions of organization, humanism, and patient-centric conditions.

[3] Masood et al. (2018) investigate patient privacy regarding Patient Physiological Parameters (PPPs), the most extensively accessed and utilised Personal Health Information (PHI) attributes within hospitals. They find that their utilisation by the various medical entities for treatment and diagnosis creates a real threat to patient privacy. This research gathers empirical evidence about PPPs usage that can benefit health technology and improve policy development on patient privacy.

[4] Yaseen et al. (2017) surveys security issues of patient monitoring sensors' data acquisition and transmission protocols. Twelve data communication protocols are reviewed and compared, including MAC layer, network layer and key management protocols. After analysing the protocols, 16 open issues are identified that disclose the need for a comprehensive and flexible security framework. Many security and privacy issues in healthcare systems using wireless sensors for real-time healthcare applications remain that require further research.

4.2. Treatment design: data preprocessing and modelling

[5] Menger et al. (2017) report on DEDUCE, a pattern matching method to automatically de-identify medical text written in Dutch, which is often necessary for legal and privacy reasons. DEDUCE only requires a low amount of effort to be hand tailored and de-identifies all information in the selection of PHI categories based on lookup tables, decision rules and fuzzy string matching. The method is validated on a test corpus of 200 nursing notes and 200 treatment plans, achieving a total micro-averaged precision of 0.814, a recall of 0.916 and a F1-score of 0.862.

[6] Lu and Sinnott (2017) show how semantic methods can be applied to support the formulation and enforcement of access control policy whilst ensuring that privacy leakage can be detected and prevented. The work is illustrated through a case study of a paediatric type-1 diabetes data registry. They demonstrate how the eXtensible Access Control Markup Language (XACML) can be extended with semantic capabilities to support finer-grained access control encompassing data risk disclosure mechanisms.

[7] Keikhosrokiani et al. (2017) Coronary Heart Disease (CHD) is the number one killer disease, for which iHeart is proposed as a patient-centric, location-based mobile cardiac emergency system to monitor and track patients via a wearable device and their mobile phones. Healthcare professionals' opinions were surveyed to uncover iHeart's success factors ($n = 323$). Structural Equation Modelling (SEM) for multi-group comparison was applied to find country-specific differences. Factors revealed include nationality, national culture, technological advancements, facilities, and the needs of the target users.

[8] Pinheiro et al. (2017) presents a hybrid model for the early diagnosis of Alzheimer's disease by applying methods of Verbal Decision Analysis structured considering the methods ARACE and NORCLASS. It approaches this decision making process in two stages. First, a classification method determines which questionnaires from a set would, themselves, detect the Alzheimer's disease. Then, the questionnaires classified as the ones that would give this diagnosis will be ordered on likeliness to speed up the diagnosis process, or at least use an ordination methodology.

[9] Yachana et al. (2017) propose a Trust-based Access Control (TAC) system which not only identifies authorised users for Patient Centric Big Medical Data (PCBMD) but also defends Sensitive Personal Information (SPI) of a patient from insider attacks. This model calculates the trust value of each user by considering various quantitative parameters. Based on the calculated trust values, access rights are granted to each user such that SPI can be accessed by only highly trustworthy users. To implement access rights securely, a privacy scheme is also proposed.

[10] Haraty et al. (2017) focuses on business continuity challenges in healthcare systems such as hacking, denial of service attacks and malicious transactions. Therefore, this research presents a high-performance damage assessment and recovery algorithm for e-healthcare systems. It is about six times faster than the most recently proposed algorithm. In the best case, it even performs 86 times faster than the current state-of-the-art. Saving the damage assessment time means shorter denial of service periods, which in turn guarantees the continuity of the patient centric healthcare system.

4.3. Treatment validation: model evaluation and knowledge deployment

[11] Kao et al. (2017) address the pervasiveness of chronic illness by exploring the design, value creation, development and evaluation of telecare systems and mobile health applications for autonomous health management. Their individual home self-care service model is implemented as an Android app and integrates six kinds of healthcare services. Usability testing is conducted to reflect five constructs: system usefulness, ease of learning, information quality, interface quality, and overall satisfaction. Experimental results are in line with the Chronic Care Model.

[12] Hossain et al. (2017) describe a framework for cloud-based rehabilitation services, which uses Augmented Reality (AR) technology along with other sensory technologies. The prototype uses the mechanism of sensor gloves to recognize gestures,

detecting the real-time condition of a patient doing rehabilitative exercises. This prototype framework found statistically significant differences between the forces exerted by patients' fingers at week one compared to week six. Significant improvements in finger strength were found after six weeks of therapeutic rehabilitative exercises.

[13] Mata et al. (2017) develop a social semantic mobile framework for physical workout exercises for personalised recommendations. Its mobile application implements the ontologies relating to health, nutrition and training domains to evaluate the physical and health condition of a runner, and to generate personalised plans. Machine learning is incorporated to process feedback using spatio-temporal analysis. Finally, the training and nutrition plans were validated by specialists, which demonstrate 82% effectiveness in exercise training routines and 86% in nutrition plans.

[14] Wautelet et al. (2017) build a Multi-Agent System (MAS)-based software solution to ensure real-time patient support during the entire stay in the hospital, in terms of bed occupancy, appointments with doctors and for medico-technical exams. They take a socio-technical approach in mapping, at runtime, the patient-centric working processes of a Belgian hospital. The MAS implementation also supports managerial decision making (*i.e.* business intelligence). Finally, the relevance to the hospital's governance is studied.

[15] Alhalabi (2017) report on the design and implementation of a 32-channel cost-effective data acquisition (DAQ) device for biomedical domestic applications in general, and patient monitoring in particular. The design process includes knitting the sensors in the fiber to create a wearable fabric which measure human body temperature, oxygen level around the body, ECG, EMG muscle signal and pH level detection. The implementation connects the generated data to a hospital server, from where a graphical interface and simulation functionality are available.

[16] Abbasi et al. (2017) highlights an often overlooked usage of social media, particularly in developing countries which lack state-of-the-art healthcare systems and processes to facilitate patient-centric healthcare by involving the patient for fulfilling personal healthcare needs. This work studies the request and dissemination behavior of people using social media to fulfil blood donation requests, uncovering that the seven twitter accounts under investigation have around 35,000 followers and receive about 900 donation requests per day.

[17] Wanderley et al. (2017) address non-adherence to medication prescriptions in Parkinson's disease (PD) patients in the CON-SIGNELA project. First, patient cognitive processes are analysed while consulting a prescription on a tablet. Second, a pilot study was carried out with young adults which confirmed the facilitating effect of table format. Finally, an app was developed from a System of Systems (SoS) perspective for patients and healthcare providers which connects a virtual pillbox, a Multi-Agent System (MAS) and a knowledge platform that capitalises on all assembled information.

5. Proclamation: the post-algorithmic era

Based on the elaborations provided above we argue that data science as a research area should accommodate applied data science as a novel research dimension that focuses more on upscaling and commoditisation requirements, which are increasingly imposed by societal needs. As Davenport and Patil (2012) already noted, there is a huge shortage of qualified data scientists. Therefore, we observe a dire need with an immense potential societal impact to empower domain experts to discover knowledge within their own, familiar data collections as much as possible. Note that such an approach does not target the same audience as in so-called *citizen data science*, in which a more democratised approach to big data and analytics is pursued by empowering *end* users who solve data science problems using automated tools without coding. We interpret the rise of applied data science and citizen data science as emerging research disciplines as the onset of the *post-algorithmic era*, where non-data scientists are empowered with automated software tools and meta-algorithmic models to self-service their own data analyses on their own data sources in a reliable, usable and transparent manner. We expect that in healthcare this development will increasingly empower physicians to perform exploratory and confirmatory patient data analyses themselves, as well as empower patients to perform periodic health reviews and continuous monitoring based on IoT, mobile, wearable and health record data.

Nevertheless, we want to emphasise that the arrival of the *post-algorithmic era* does not preclude more theoretical data science as an ever-important research area. We foresee a continued need for novel algorithms to solve optimisation problems, for example. However, we do argue that for typical exploratory data analysis (EDA) tasks we now have a sufficiently large inventory of available algorithms at hand which can be effectively reused at will, iff appropriate insight into their intended usage and performance can be provided transparently, for which we here propose meta-algorithmic modelling as a communicative means to empower a much broader professional audience to leverage the "new oil".

6. Advanced telematics and informatics research for next generation data science

The integrative research on patient-centric healthcare is an opportunity for the scientific computer science and information systems research community to represent their adoption or fusion of novel data mining research in the field of smart healthcare analytics. More specifically, using the advancement of telematics and informatics as a research foundation, the key inquiry is to discuss how:

- pattern analyses should be conducted and designed to better understand big data in the realm of healthcare;
- to conduct big data-driven pattern analyses on longitudinal data;
- to integrate heterogeneous systems;
- to develop frameworks to make all data meaningful, accessible and available everywhere and permanently;

- to develop Automatic Identification and Data Collectors systems;
- to develop intelligent systems to support transparent and robust clinical decisions;
- to deal with various social issues in the adoption of telematics in medicine and healthcare.

These technologies improve the quality of resources available to individuals within the areas of medicine, patient care, and healthcare. They can help to mitigate financial crises, clinical risks and human social factors. At the same time, individuals in business, patients, and learners will be part of the process, having more information delivered to their mobile devices instantly. Stockholders, educators, medical experts, service designers and technology-intensive innovators will have more information to deliver smart services and to promote competitive advantage. This is, in fact, a new era of radical innovation based on data-sensitive applications, capable of exploiting leading-edge approaches in software engineering and data mining. The Next Generation of Patient-Centric Healthcare needs to examine these intertwined pillars (*i.e.* Business, Healthcare, Education and Policy Making) and the challenges that data science researchers encounter as they attempt to capture, store and utilise human data. Considering these developments, this Special Issue contributes significantly in the body of knowledge and publishes new and innovative techniques and methodologies in the field of Patient-Centric Healthcare and Advanced Telematics and Informatics Research.

The following are some of the most promising areas of research for:

- Integration of advanced software engineering methods and data mining fuzzy models for humanistic social problems (Visvizi et al., 2017);
- Interdisciplinary advanced semantic engineering and social sciences research (Lytras et al., 2017);
- Provision of smart, ubiquitous patient-centric services towards a smart cities vision (Torres-Ruiz and Lytras, 2016);
- Cognitive computing and software engineering integrative methods for advanced computational intelligence for Telematics and Informatics applications in medicine and healthcare;
- Big Data mining over distributed social networks and machine learning enhancements for personalised medicine;
- Software engineering advanced skills and competencies-based training towards new generation collaborative teams in the healthcare domain;
- Innovation networks enabled by sophisticated telematics and informatics methods, and per matching mining for large scale distributed cloud applications;
- Software quality metrics, learning analytics and key performance indicators for smart software engineering in medicine and patient-centric healthcare;
- Sustainable software engineering for social inclusive development and smart healthcare.

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