

Smart Data as a Service

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Abstract. Nowadays, smart data emerge as a new research direction to create value from business data in an intelligent way. Smart data are defined as the data gathered and processed that can be used to create new insights for smart solutions to support business strategies. This paper aims at proposing a conceptual model for smart data management. In other words, the model can be used for designing a smart service system based on the perspective of service science that can manage and deliver smart data as a service.

1. Introduction

Nowadays, the new development of big data, business analytics, and artificial intelligence has fundamentally changed traditional business processes [1, 2]. Enterprises are under pressure to innovate and create unique and exceptional competitive advantages. One of the most important challenges faced by enterprises is how to create value from business data, especially big data [3, 4]. Smart data are defined as the data gathered and processed that can be used to generate new insights for smart solutions to support business strategies [5, 6].

This paper aims at expanding knowledge regarding the management of smart data in today's business landscape in order to develop new intelligence of smart data and solutions in the era of big data and artificial intelligence. Smart solutions, which are built based on smart data and intelligent systems and services, have the capacity of self-detecting and self-adaptation to users' needs without their explicit requests [5, 7]. Big data, business analytics, the Internet of Things, and cloud computing provide a huge source of knowledge that needs to be transformed into smart data, to determine user contexts, and then to enable intelligence capabilities of smart solutions [5, 8].

However, there is still a little focus on how to transform big data into a higher level of data that can be used for smart solutions [6, 9]. For this reason, this paper aims at proposing a conceptual model for designing a smart service system, which can manage and deliver smart data as a service. Based on the service science perspective, smart data management is an emerging research direction that concerns the management, the science, and the engineering of smart data [10-12].

The paper is structured as follows. Section 2 continues with the principles of smart data. Section 3 presents the actionable insights and the challenges of the transformation from smart data to actionable insights. Section 4 proposes the conceptual model for smart data management and Section 5 ends with the conclusion and future work.

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2. Smart data

Enterprises are overwhelmed with big data; however, big data are not important if no insights are extracted [12, 13]. In a sense, smart data mean the “right data” that can reveal insights and make these insights actionable. Smart data are the combination of big data and deep data [8, 14]. Deep data can provide the context and calibration of a researched phenomenon that is a challenge of big data [12, 14]. To put it another way, big data are perceived as smart data when they can generate meaningful insights and create value [5]. Analytics transforms meaningless numbers into actionable insights. From the perspective of analytic techniques, patterns and insights of smart data are extracted by intelligent algorithms [6]. With the support of state-of-art analytics, smart data can be generated at the point of data collection [8]. Therefore, enterprises can reduce costs for data storage [3]. The real-time attribute of smart data also leverages the value of big data through various decision supports [4, 14]. Building from these reflections, this study defines smart data as a subset of big data that can provide actionable insights through the process of analytics [5, 6, 12].

In terms of significance, smart data respond to the challenges of big data that most enterprises encounter [6]. In particular, smart data deal with the problems of data overload and data quality due to the characteristics of big data such as huge volume, velocity, veracity, and variety [9, 10]. In accordance with this view, the study of García, Ramírez-Gallego, Luengo, Benítez and Herrera [11] defines smart data as an important step of data preprocessing to provide a smart dataset in a timely and accurate manner. Accordingly, adopting smart data helps enterprises determine the most current and relevant data sources as all data sources are not equal [15]. Actually, focusing on the right data source can improve the quality of data.

3. From smart data to actionable insights

As discussed in the previous part, smart data outperform big data as they provide actionable insights [5, 6, 12]. Actionable insights are defined as meaningful findings through the process of data analytics. Enterprises rely on actionable insights for data-driven decisions [18]. With the supports of actionable insights, enterprises are enlightened with actions that need to be taken in dealing with complex business situations [6, 19].

Not all insights are actionable [6]. Insights are actionable in the sense that enterprises can draw conclusions and take actions upon business situations [18, 20]. In fact, about 70% of enterprises struggle with taking data analytics to the next step for action plans [21].

In other words, actionable insights are the gap between data and business value [22]. This stimulates the motivation to clarify factors that support actionable insights. Firstly, actionable insights should be aligned with the goals and strategies of an enterprise to drive actions [23]. Secondly, insights are actionable by being aware of the context or circumstances of service providers (e.g.: organizational culture, strategies, capacities) and customers (e.g.: time, location, preference, etc.) [18, 24]. Accordingly, a service solution can be recommended to the right customer at the right time in the right setting [1, 10]. Finally, actionable insights should be specific, clear, critical, and innovative so that decision-makers are stimulated to act upon them [25, 26]. These characteristics of actionable insights make enterprises comprehensively understand an insight, its importance, priority, and feasibility [27]. The literature points out that insights are not well manifested towards models or business rules/processes [19, 28]. Actionable insights need to be visualized through digital dashboards or models to support the decision-making process [20, 29].

4. Conceptual model for smart data management

This section presents a conceptual model for smart data management that set the foundation for designing a smart service system from the perspective of service science. A smart service system is a context-aware service system, which can dynamically adapt to a context and support the decision-making process for a specific business situation [32]. This perspective comprises three elements: science, management, and engineering [30].

Figure 1 illustrates the conceptual model for smart data management, including the engineering, science, and management elements.

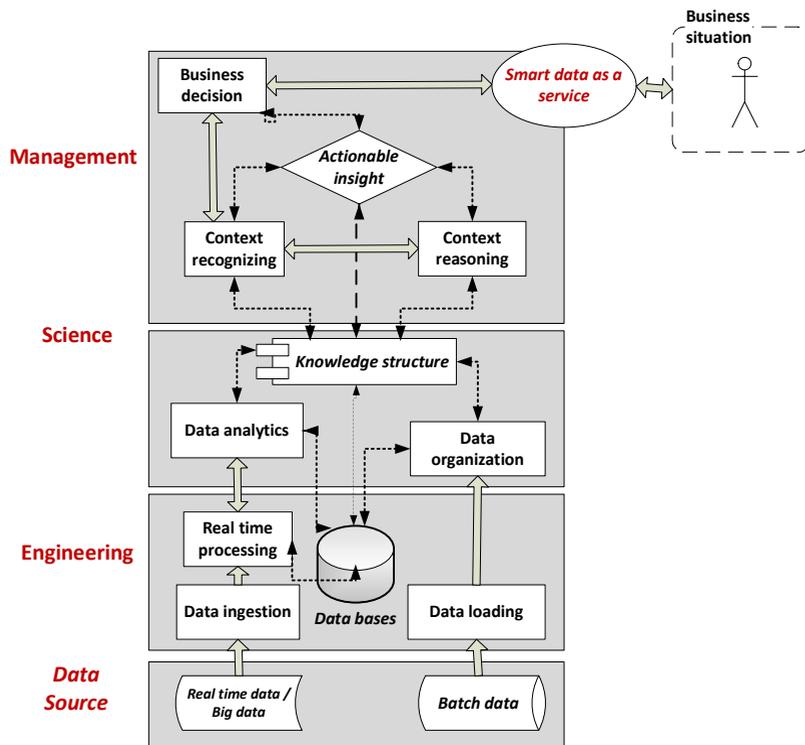


Fig. 1. Conceptual model for smart data management.

Engineering element. The engineering element, which aims at capturing different types of data, covers the invention of new technologies to obtain big data and deep data from different data sources and transform them into useful data stored in database management systems [30]. The new sources of data and techniques for data capturing can improve the quality of business services and create new innovative services related to smart data. This element includes components such as *data loading*, *data ingestion*, and *real-time processing* components to process different data sources to support data collection, provision, and distribution model [31].

Science element. The science element, which focuses on organizing data into useful information, deals with the structure of service systems and facilitates the process of service creation and the application of competencies [30]. A knowledge structure is defined as an interrelated collection of concepts of a domain, relationships between concepts, and relationships between concepts and a data source. In our approach, concepts are defined by different knowledge components such as know-what, know-how, know-why, know-where, know-when, know-who, and know-with [31, 32]. The *data analytics* and *data organization*

components help to discover new types of data and knowledge, to link data sources with relevant concepts and determine relationships between concepts.

Management element. The management element, which aims at transforming useful information into actionable insights, concerns methods and techniques to improve services related to smart data through effective management [30]. The objectives of this element focus on the control, discovery, collaboration, learning, and decision support based on actionable insights [31]. Smart data as a service provide a service to a decision-maker based on a particular business situation. The *context recognizing* and *context reasoning* components help the *business decision* component to determine the context of the corresponding business situation. A context is defined as “a stakeholder (know-who) performs actions (know-how) on objects (know-what) at a certain time (know-when) in a location (know-where) because of a contract (know-with) to be consistent with a business rule (know-why)” [32]. Thus, the *business decision* component may provide the possible solutions and recommend a specific solution based on business intelligence and analytics techniques performing on actionable insights and related data sources.

5. Conclusion

This paper proposes a conceptual model for designing a smart service system based on the perspective of service science that can manage and deliver smart data as a service. It is believed that this study is one of the first that focuses on supporting smart data management from the service science perspective.

Concerning the implications of our work for practice, the proposed model sets a strong foundation for change management on smart data and for organizational adaptation on business structure and systems to support smart data. In fact, smart data also facilitate the need for managerial, organizational, and technological changes corresponding to the management, science, and engineering elements of the model [10-12]. The management changes focus on developing business strategies to offer context-aware smart services [16, 17]. The organizational changes address the significance of organizational culture, structure, business process, and leadership for smart data management [5, 7]. The technological changes emphasize the need for automation tools for collecting and transforming big data and deep data for smart data capture [8, 10]. In summary, the ultimate importance of smart data is its transformation of enterprises that struggle with data into data-driven enterprises for smart solutions [3, 4].

Concerning the implications of our work for research, the proposed model can be a starting point for studies on smart data management and application in business. We are currently developing the framework for smart data management based on our previous work [32] under the informational lights of service science for the progression [33].

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