

Characterizing the Capabilities of Internet of Things Analytics Through Taxonomy and Reference Architecture: Insights From Content Analysis of the Voice of Practitioners

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ABSTRACT

The increasing prevalence of business cases utilizing internet of things (IoT) analytics, coupled with the diversity of IoT analytics platforms and their capabilities, poses an immense challenge for organizations seeking to make the best choice of IoT analytics platform for their specific use cases. Aiming to characterize the capabilities of IoT analytics, this article presents a reference architecture for IoT analytics platforms created through a qualitative content analysis of online reviews and published implementation architectures of IoT analytics platforms. A further contribution is a taxonomy of the functional and cross-functional capabilities of IoT analytics platforms derived from the analysis of published use cases and related business surveys. Both the reference architecture and the associated taxonomy provide a theoretical basis for further research into IoT analytics capabilities and should therefore facilitate the evaluation, selection, and adoption of IoT analytics solutions through a unified description of their capabilities and functional requirements.

KEYWORDS

Classification, Content Analysis, Data Analytics, Internet of Things (IoT), IoT Analytics, Online Reviews, Reference Architecture, Taxonomy, Voice of Practitioners

INTRODUCTION

The Internet of Things (IoT), which connects physical objects with the virtual world, is considered one of the key technologies that enable and drive digital transformation, as the ability of IoT devices to capture and transmit data over networks and connectivity creates vast amounts of data that is generating substantial benefits for organizations (Marjani et al., 2017). The growing number of sensors, actuators and tags used in various areas of daily life, business and industry play a central role in a variety of applications characterized by generic terms such as “Industry 4.0”, “Smart City” and “Smart Home” (Ben-Daya, Hassini, & Bahroun, 2019; Yassine, Singh, Hossain, & Muhammad, 2019). These describe complex fields of application that not only attempt to digitize and optimize existing business and industrial processes using smart devices, but also create entirely new business and consumer application scenarios (Adi, Anwar, Baig, & Zeadally, 2020). Economic analysts predict that by 2023, 30% of companies in various industries will fully deploy on-premise IoT technologies and that the size of the global IoT market will grow to \$800 billion (Gartner, 2019; Lheureux et al., 2020).

DOI: 10.4018/JITR.299929

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With the increasing number of embedded sensors, actuators and things connected to the Internet, the amount of data generated by IoT devices is also growing rapidly. Today, this data is becoming a critical asset that provides valuable opportunities for companies to grow, innovate and sustain a competitive advantage (Garg & Garg, 2020; Siow, Tiropanis, & Hall, 2018). However, it also poses an immense challenge in terms of data management, storage and analysis. In this context, data analytics of IoT data plays a crucial role in today's IoT domains and will be even more relevant in the future (Adi et al., 2020). The main objective of IoT analytics is to generate knowledge and context from data streams generated by a large number of heterogeneous devices to enable various IoT applications (Yassine et al., 2019). IoT analytics is described as a process in which a large amount of IoT data is analyzed to uncover trends, patterns, correlations and valuable insights to support decision making at both strategic and operational levels (ur Rehman et al., 2019). Depending on the type of IoT applications and business requirements, such analysis can be performed either by humans or by artificial intelligence and machine learning (AI / ML) in real time or over a longer period of time (Gupta & Jain, 2020; Minter, 2017).

As IoT continues to flourish and grow in importance, the value of IoT analytics platforms as an integral part of the IoT ecosystem is gaining increasing interest with implications for almost all areas of technology and business. IoT analytics platforms are specialized platforms for collecting, processing, storing, and analyzing data from IoT devices (Gartner, 2019). Today, many industries leverage IoT analytics platforms and services to understand real-time consumer needs, improve responsiveness, streamline processes and identify innovative business models to support their digital transformation strategy (Ben-Daya et al., 2019; Nicolescu, Huth, Radanliev, & De Roure, 2018). The prominence of IoT analytics platforms can also be witnessed from the size of the associated market. For example, the Boston Consulting Group estimates that in 2020 a total of \$250 billion will be spent worldwide on the Internet of Things, of which \$15 billion will be spent on IoT analytics platforms (Hunke et al., 2017). Due to this market potential, more than 450 providers are currently competing with each other (Gartner, 2019; Hunke et al., 2017; Williams & Lueth, 2017). This diversity, combined with the fact that IoT analytics represents complex solutions and different platforms have different capabilities, leads to an opaque and fragmented market (Williams & Lueth, 2017). As a result, prospective adopters are faced with the fact that despite this diversity, no single IoT analytics platform is equally well suited for every IoT application scenario (Siow et al., 2018). In addition, organizations seeking to exploit the benefits of IoT applications while continuing to maintain their existing IT infrastructure are confronted with the challenge of making the best choice of IoT analytics platform for their specific business requirements from the wide range of candidates available on the market (Fati, Jaradat, Abunadi, & Mohammed, 2020; Soldatos, 2017).

The capabilities of IoT analytics platforms are an essential evaluation and selection criterion (Siow et al., 2018). However, in order to understand the capabilities of the various IoT analytics platforms available on the market, practitioners have to compile and evaluate numerous documents with heterogeneous descriptions at different levels of abstraction from different sources. Therefore, any comparison of the capabilities of different IoT analytics platforms is not easily possible on this basis. For many companies planning to develop smart products and services, the key issue facing them at present is how to make it easier to establish or expand IoT activities in a practical and sustainable way (Nicolescu et al., 2018; Sethi & Sarangi, 2017). Numerous technical and organizational challenges are involved, from device management and data storage to data analysis and development of smart services (Brous, Janssen, & Herder, 2020). Furthermore, a wide range of different technologies and heterogeneous architectures have been used in the implementation of IoT analytics use cases (Mahdavejad et al., 2018; Marjani et al., 2017; Pääkkönen & Pakkala, 2020; Ray, 2018). With the goal of helping to solve this problem, this work has mainly focused on describing the architectures of individual contributions from several major vendors (e.g., Amazon, Microsoft, and Google) and has examined specific end-user applications such as machine health monitoring or factory efficiency or effectiveness (OEE) analysis (Siow et al., 2018). At the same time, work merging the individual architectures into a coherent reference architecture is limited, although early contributions exist (O'Donovan, Bruton, & O'Sullivan, 2016; Pradeep, Balasubramani, Martis, & Sannidhan, 2020;

Sethi & Sarangi, 2017; Tesch, Brillinger, & Bilgeri, 2017; ur Rehman et al., 2019). Therefore, the development of a technology-independent reference architecture and the classification of associated implementation technologies and services would be valuable for the exploration and deployment of IoT analytics applications and systems in enterprises.

The main contribution of this article is to provide a unified description of the capabilities of IoT analytics platforms through a coherent reference architecture and taxonomy by analyzing the voice of IoT and data analytics practitioners. The potential capabilities were primarily identified through a qualitative content analysis of online user reviews collected from Gartner.com, a leading research and consulting firm that publishes online reviews of enterprise IT software and services (Gartner, 2019). In addition to online reviews, data was compiled from a variety of resources, including relevant documents and literature, official websites, product brochures, and company surveys. The resulting capabilities were then integrated and organized into a hierarchical taxonomy upon which a reference architecture was built. The goal of the reference architecture and associated taxonomy is to enable better understanding and articulation of insights into the capabilities of IoT analytics platforms. They are also intended to provide practical guidance for practitioners to analyze the system functionality of IoT analytics platforms and create a foundation for comparing the functional capabilities of various IoT analytics platforms available in the market. The findings from this article offer several important theoretical and practical implications and should therefore serve as a valuable resource for gaining insight into the design, evaluation, and application of IoT analytics platforms in organizations.

The remainder of this article is structured as follows. Section 2 examines related work on the specifics of IoT analytics, as well as previous work on taxonomies and reference architectures for IoT analytics platforms. Section 3 discusses how a taxonomy and reference architecture has been developed to characterize the capabilities of IoT analytics platforms using a qualitative content analysis of online reviews and relevant literature. Section 4 then illustrates how the developed reference architecture can be applied in projects to evaluate and select the most appropriate IoT analytics platform from a range of candidates. Section 5 presents the implications for research and practice, followed by a discussion of the limitations and prospects for future research. Finally, Section 6 concludes this article.

RELATED WORK

Specifics of IoT Analytics

To understand the specifics and nuances of IoT analytics, it is helpful and relevant to divide it into two parts and define both IoT and data analytics separately. The term “Internet of Things” (IoT) describes the network of physical objects (things) embedded in sensors, software and other technologies that enable objects to communicate, collect data and exchange information with other devices and systems over the Internet (Boyes, Hallaq, Cunningham, & Watson, 2018; Dorsemaine, Gaulier, Wary, Kheir, & Urien, 2015; Elijah, Rahman, Orikumhi, Leow, & Hindia, 2018). The combination of sensor and actuator devices enables the sharing of information across platforms through a unified architecture and the development of a common operating landscape to enable innovative applications (Adi et al., 2020; Belhadi, Zkik, Cherrafi, Yusof, & El fezazi, 2019; Bibri, 2018). With affordable computing solutions, the cloud, big data, and mobile technologies, physical objects can share and collect data with minimal human intervention. In this hyper-connected environment, IoT technologies can record, monitor, and analyze every interaction between connected objects. The physical world meets and collaborates with the digital world (Dai, Wang, Xu, Wan, & Imran, 2019; Elijah et al., 2018).

The IoT’s inherent ability to create a network of smart sensors capable of collecting and analyzing valuable information across multiple environments is driving a wide range of applications. Common applications of IoT include smart manufacturing, predictive and predictive maintenance, smart energy grids, smart cities, connected and smart logistics, and smart digital supply chains (Oztemel & Gursev, 2020; Siow et al., 2018; Sjödin, Parida, Leksell, & Petrovic, 2018; Tesch et al., 2017; Yassine et al., 2019). Recent studies show that the development of smart devices is not stagnating (Banerjee &

Woerner, 2017; Bansal & Kumar, 2020; Nicolescu et al., 2018). On the contrary, there will be more than 500 billion smart devices on the market worldwide by 2030, generating sales of up to \$1.5 trillion (Mahdaveinejad et al., 2018; Muccini, Spalazzese, Moghaddam, & Sharaf, 2018). As IoT continues to expand in the marketplace, companies can benefit from the tremendous business value it can deliver. With the advent of the cloud and related technologies such as data analytics, artificial intelligence and machine learning, companies across a wide range of industries can achieve new levels of automation, increase business process productivity and efficiency, create new revenue opportunities and develop new business models (Bibri, 2018; Biswas, Dupont, & Pham, 2017; Elijah et al., 2018).

The term data analytics, as originally coined by Davenport and Harris (2007), refers to a set of business intelligence and analytics (BI&A) technologies that are primarily concerned with data mining and statistical analysis. Although several definitions are presented in the literature (e.g., Davenport & Harris, 2007; Davenport & Kim, 2013; Eggert & Alberts, 2020), the general and common idea remains the same. Chen, Chiang, and Storey (2012) described data analytics as the process of deriving knowledge and actionable insights from data using quantitative, statistical, or predictive models to help executives, managers and other business users make informed business decisions. Although there is a synergistic relationship between data analytics and IoT that allows them to leverage large amounts of data collected from various sources in a structured and unstructured format, only through IoT analytics systems can companies combine and integrate all types of IoT data to gain insights at all levels of the enterprise (Côrte-Real, Ruivo, & Oliveira, 2020; Guilfoyle, 2020). One of the most distinctive features of IoT analytics is its ability to analyze IoT data, which is typically unstructured in nature. This makes it unsuitable for traditional analytics and business intelligence tools designed to process structured data. IoT data comes from devices that often record relatively noisy processes (e.g., temperature, motion, or sound). Data from these devices can often have significant gaps, corrupted messages, and erroneous readings that need to be cleaned up prior to analysis (Grossman, 2018; Velosa & Kutnick, 2016). IoT analytics enables the processing of a large amount of data on the fly and facilitates the storage of data in various storage technologies that are automatically saved for later processing or reintegration for another application. Given the large amount of unstructured data collected directly from web-enabled devices, IoT analytics implementations require instant analysis with real-time queries to help organizations quickly gain insights, make quick decisions, and interact with people and other devices (Marjani et al., 2017).

With the ever-growing wealth of data generated by IoT devices, IoT analytics is rapidly becoming a key enabler for decision-making at both strategic and operational levels. By providing insights into various areas such as customer relationships, marketing, inventory management, product and service development, and other core business areas, the use of IoT analytics platforms enables innovation and the creation of sustainable competitive advantage (Ben-Daya et al., 2019; Shakeel, Mardani, Chofreh, Goni, & Klemeš, 2020). By combining IoT sensors and data analytics technologies, companies can increase operational efficiency, reduce costs, develop value-added services, and ultimately increase profitability (Goni et al., 2020). A recent survey by SAS (SAS, 2020) found that 93% of companies that invested in IoT and data analytics achieved cost savings, while 91% of companies that invested in IoT improved their competitive advantage. Data analytics and IoT are capable of transforming our economy and society. Their contribution is expected to be of great importance in transforming many companies into digital enterprises in the era of digitalization and Industry 4.0 (Côrte-Real et al., 2020; Ibarra, Ganzarain, & Igartua, 2018; Tesch et al., 2017).

According to the requirements of IoT applications, different types of analytics are used. These types and levels of analytics are discussed in the relevant literature under the categories of real-time, offline, storage, business intelligence (BI), and big data analytics (Adi et al., 2020; Marjani et al., 2017). Typical data mining methods applied to data related to IoT and intelligent services include cluster analysis, classification, association analysis and regression analysis. Machine learning and artificial intelligence methods are also helpful in the analysis of mass IoT data. Approaches such as the Lambda architecture describe the analytical approach to big data using data mining and different

variants that can be used in this context (Kolajo, Daramola, & Adebisi, 2019). However, with the exception of a few large information-centric companies such as Microsoft, Amazon, and Google that are actively using IoT analytics, most large and mid-sized companies are still in an embryonic stage of adoption and are struggling to understand and define their IoT analytics strategy. In addition, many business leaders are hesitant to invest in IoT analytics because their past experiences with business intelligence and analytics initiatives have shown unsatisfactory results (Côrte-Real et al., 2020).

Taxonomies and Reference Architectures for IoT Analytics Platforms

In the context of IoT analytics, taxonomies play an important role in research and practice because classifying IoT analytics capabilities through a taxonomy helps organizations understand and analyze individual characteristics of different IoT analytics platforms (Alkhabbas, Spalazzese, & Davidsson, 2019). The taxonomy of IoT analytics can also help structure and organize otherwise fragmented concepts and enable researchers to postulate about the relationships between these concepts (Pääkkönen & Pakkala, 2015). At the same time, the taxonomy of IoT analytics can be understood both as a standalone framework and as a foundation for the development of further taxonomies (ur Rehman et al., 2019). In addition, the taxonomy can serve as a reference architecture that typically describes and allows for a variety of different implementations of IoT analytics and supports its goal of standardization (Siow et al., 2018). Reference architectures can in turn be used for screening, evaluating, and comparing different IoT analytics solutions (Pääkkönen & Pakkala, 2020).

The architectural concept of IoT analytics comprises several design descriptions based on the abstraction and identification of IoT application areas. It provides a reference model that describes the relationships between different IoT environments, such as smart traffic, smart home, smart transport, and smart health. Several IoT analytics architectures can be found in the literature (Adi et al., 2020; da Cruz, Rodrigues, Al-Muhtadi, Korotaev, & de Albuquerque, 2018; Sethi & Sarangi, 2017; Siow et al., 2018). For example, da Cruz et al. (2018) presented an IoT analytics architecture with cloud computing at its core and a model of end-to-end interaction between different stakeholders in a cloud-centered IoT framework to enable better comparison with other IoT analytics platforms. This architecture provides a seamless, ubiquitous collection, analysis, and presentation of information through a unifying architecture of IoT. However, the current architecture focuses on IoT in terms of communication and less on the analytical capabilities and functionality of IoT analytics.

Several previous studies have focused on the development of taxonomies or reference architectures for IoT analytics platforms (e.g., Crook & Vesset, 2020; Guth et al., 2018; Siow et al., 2018; ur Rehman et al., 2019). Among these studies are the two articles by Sethi and Sarangi (2017) and Marjani et al. (2017), which build on each other and derive an abstract software architecture for IoT analytics platforms from a small number of research projects. The work of da Cruz et al. (2018), Guth et al. (2018) and Siow et al. (2018) suggests different reference architectures for IoT and the data analytics ecosystem. In these reference architectures, IoT analytics platforms are integrated with other components of an IoT ecosystem only at a relatively high level of abstraction, with limited reference to their capabilities. Drawing upon a reference architecture for Industry 4.0 and using a questionnaire survey, Nagy, Oláh, Erdei, Máté, and Popp (2018) identifies three different categories of IoT analytics that differ in their architecture and assigns 13 selected IoT analytics platforms to these categories. The article by Hodapp, Remane, Hanelt, and Kolbe (2019) presents a taxonomy for business models of IoT analytics platforms that only mentions their capabilities in passing.

While several studies have characterized IoT analytics systems by taxonomies, these taxonomies are either defined on an abstract level (e.g., Alkhabbas et al., 2019; da Cruz et al., 2018; Guth et al., 2018) or take a specific perspective or category of IoT analytics systems (e.g., Marjani et al., 2017; Nemeth, Ansari, Sihn, Haslhofer, & Schindler, 2018; Pääkkönen & Pakkala, 2020; Soldatos, 2017). Alkhabbas et al. (2019) proposed a taxonomy for facilitating the understanding of IoT and analytics ecosystems. The taxonomy classifies IoT devices based on their architectural characteristics while considering security aspects. In addition, the authors provided a procedure to validate the completeness,

accuracy, and timelessness of the proposed taxonomy. While they focused on individual IoT devices, this article adopts a systematic perspective that leads to a more holistic view of IoT analysis systems. In addition, this article has conducted a systematic review that analyzes various taxonomies found in the literature. A number of conceptual models for IoT analysis systems have been proposed in the literature. For example, Alexopoulos, Koukas, Boli, and Mourtzis (2018) presented an architecture for IoT analytics systems to support the analysis phases of services in industrial product-service systems. Yassine et al. (2019) presented a conceptual model for applications of IoT analytics in smart homes and fog computing. Following Elijah et al. (2018), ur Rehman et al. (2019) proposed a conceptual model for business-critical IoT analytics systems. Although these models capture the capabilities identified in this article to varying degrees, none of them offers a comprehensive examination of the capabilities of IoT analytics platforms and their specific characteristics from the perspective of practitioners.

A similar picture emerges when reviewing the non-academic literature. For example, the software development documentations of Azure IoT analytics (Microsoft, 2018), AWS IoT Analytics (Amazon, 2020), and SAS IoT analytics (SAS, 2020) describe reference architectures that cannot be regarded as generally valid and only describe the ecosystem of the respective in-house IoT analytics platforms. The white paper by Crook and Vesset (2020) describes a taxonomy and an associated reference architecture for IoT analytics platforms; however, it does not describe the methodology used in its creation, making it unclear whether IoT analytics platforms can be fully described based on this taxonomy. The same restriction applies to the abstract architecture for IoT analytics platforms described in a white paper by Hilton (2018). In a market study by Gartner (2019), a wide range of functional and non-functional characteristics of IoT analytics platforms are presented based on a survey of various providers. Similarly, the market study by IoT Analytics (2017) classifies the functional and non-functional capabilities of eight IoT analytics platforms for manufacturing and industry 4.0 into an architectural reference model based on a survey. Table 1 presents a comparison of the above-mentioned preliminary work and classifies it systematically. To the best of the author's knowledge, the taxonomy and reference architecture proposed in this article, which is intended to provide a holistic and integrative view of IoT and data analytics, has not yet been thoroughly investigated in the current literature. Therefore, this article aims to develop a generally applicable and comprehensive taxonomy based on widely used, commercially available IoT analytics platforms, using qualitative content analysis as a research methodology.

RESEARCH METHODOLOGY

The main objective of this study is to provide a unified description of the capabilities of IoT analytics platforms through a taxonomy and reference architecture based on an analysis of the voice of practitioners and related business surveys of popular IoT analytics platforms. To this end, a qualitative content analysis approach was used to extract, analyze, and classify the textual content of practitioners' evaluations and feedback on their perceptions and experiences in using IoT analytics platforms. Qualitative content analysis is a strand of a research method that enables "the subjective interpretation of the content of textual data through the systematic classification process of coding and identifying themes or patterns" (Hsieh & Shannon, 2005). According to Nickerson, Varshney, and Muntermann (2013), qualitative content analysis is characterized by its ability to not only reveal object-related individual elements, but also allow replicable and valid conclusions to be drawn from the data to provide knowledge, new insights, and a description of phenomena. A key advantage of qualitative content analysis is that it enables processing and inductive use of large amounts of textual data to find evidence. It also enables an in-depth analysis of context and process elements as well as activities of the key users involved in the implementation process (Daradkeh, 2019a, 2019b; Daradkeh & Sabbahein, 2019). The qualitative content analysis method was deemed appropriate for this study because it allows for the flexible and adaptable collection of subjective judgments guided by in-depth exploration and analysis. Moreover, this study assumes that the opinions of practitioners

Table 1. Related work with taxonomies or reference architectures for IoT analytics platforms.

Publication	Type of Publication	Methodology	FC	NFC	#IoT	TAX	RA	#CTRA	Purpose
(da Cruz et al., 2018)	Journal article	Systematic literature review and reference modelling	✓	✓	33	–	✓	5	Reference architecture for IoT analytics systems
(Siow et al., 2018)	Journal article	survey, reference modelling	✓	✓	13	–	✓	36	Categorization of analytical approaches and proposal of a layered taxonomy of IoT analytics
(ur Rehman et al., 2019)	Journal article	Reference Modelling	✓	✓	4	–	✓	5	Categorization of IoT analytics platforms based on their capabilities
(Alkhabbas et al., 2019)	Journal article	Reference Modelling	✓	✓	8	✓	–	6	Comparison of different IoT analytics platforms using taxonomy
(Sethi & Sarangi, 2017)	Journal article	survey, reference modelling	✓	✓	8	–	✓	10	Comparison of different IoT analytics platforms using reference architecture
(Ray, 2018)	Journal article	Requirement analysis, reference modelling	✓	✓	24	–	✓	39	General description of the capabilities of IoT analytics platforms
(Adi et al., 2020)	Journal article	Requirement analysis, reference modelling	✓	✓	6	–	✓	37	General description of the functionality of IoT analytics platforms
(Marjani et al., 2017)	Journal article	survey, reference modelling	✓	✓	13	–	✓	36	Comparison of different IoT analytics platforms using reference architecture
(Mahdavinejad et al., 2018)	Journal article	survey, reference modelling	✓	✓	13	–	✓	36	Description of the capabilities of IoT analytics platforms
(Zschörnig, Wehlitz, & Franczyk, 2020)	Journal article	Reference Modelling	✓	✓	4	–	✓	5	Categorization of different IoT analytics platforms
(Saleem & Chishti, 2019)	Journal article	survey, reference modelling	✓	✓	13	–	✓	36	Comparison of different IoT analytics platforms
(Somani, Zhao, Srirama, & Buyya, 2019)	Journal article	Reference Modelling	✓	✓	8	ü	–	6	Comparison of different IoT analytics platforms
(Cirillo, Wu, Solmaz, & Kovacs, 2019)	Journal article	Reference Modelling	✓	✓	8	✓	–	6	Comparison of different IoT analytics platforms
(Guth et al., 2018)	Book Chapter	Systematic literature review and reference Modelling	✓	✓	4	–	✓	5	Comparison of different IoT analytics platforms using reference architecture
(Hodapp et al., 2019)	Book Chapter	Reference Modelling	✓	✓	190	✓	–	6	Comparison of different IoT analytics platforms using reference architecture

Table continued

Publication	Type of Publication	Methodology	FC	NFC	#IoT	TAX	RA	#CTRA	Purpose
(Bauer et al., 2013)	Book Chapter	Reference Modelling	✓	✓	8	✓	–	6	Comparison of different IoT analytics platforms using reference architecture
(Crook & Vesset, 2020)	Market research	Survey	✓	✓	33	✓	✓	6	Description of the capabilities of IoT analytics platforms
(Velosa & Kutnick, 2016)	Market research	Survey	✓	✓	24	✓	✓	6	Comparison of different IoT analytics platforms
(Microsoft, 2018)	Business Report	Not Explicit	✓	✓	1	–	✓	n.a.	Description of a specific IoT platform, namely Azure IoT Analytics, based on different architecture configurations.
(Amazon, 2020)	Business Report	Not Explicit	✓	✓	1	–	✓	13	Description of a specific IoT platform, namely AWS IoT Analytics, based on different architecture configurations.
(SAS, 2020)	Business Report	Not Explicit	✓	✓	1	–	✓	13	Description of a specific IoT platform, namely SAS Analytics for IoT, based on different architecture configurations.

FC - Functional capabilities, NFC - Non-functional capabilities, #IoT - Number of IoT analytics platforms or use cases considered, TAX - Taxonomy, RA - Reference architecture, #CTRA - Number of capabilities in the taxonomy or reference architecture, n.a. - Not applicable.

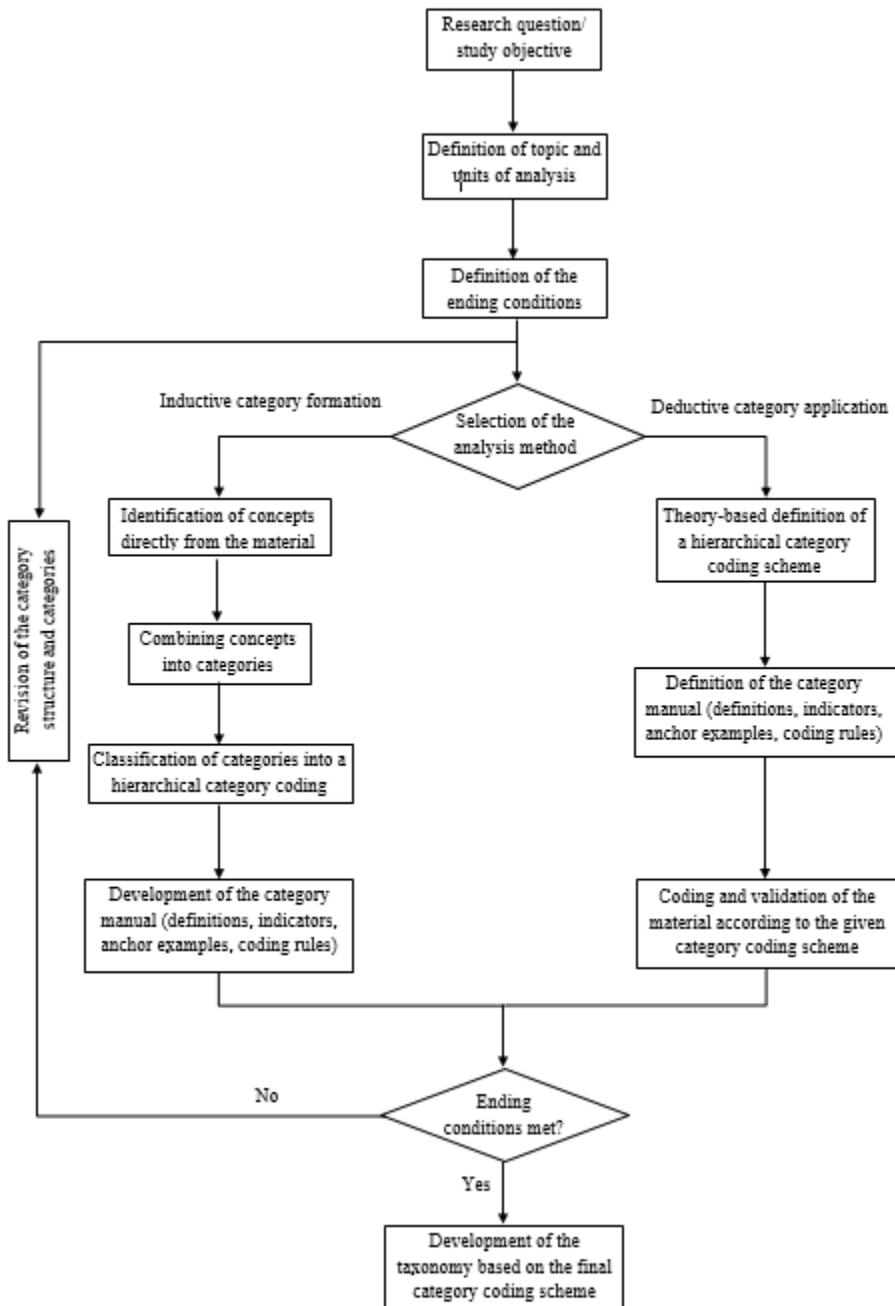
and experts can be of immense value in situations where knowledge or theory is incomplete, as in the case of exploring and classifying the capabilities of IoT analytics platforms.

Following Nickerson et al. (2013), an iterative hybrid process combining deductive and inductive analysis methods was applied. This allows for different perspectives to be adopted for gaining insights from the textual content. This process was accompanied by elements of qualitative content analysis from Vaismoradi et al. (2013), as shown in Figure 1. First, a set of criteria was defined to include or exclude a review and identify the units of analysis (i.e., individual themes) in selected online reviews. Second, an appropriate coding protocol and a process for collecting data from online reviews were developed in line with the objective of this study to identify from practitioners' feedback the capabilities of IoT analytics platforms that could influence the organization's evaluation and decision to adopt IoT analytics platforms. To improve the reliability of the assessment, both human coding and text analytics software (NVivo) were used to analyze the data. Two coders were trained based on a protocol developed specifically for this study. Finally, the results obtained were validated for consistency and inter-coder agreement reliability using Krippendorff's alpha (Krippendorff, 2012). In general, a Krippendorff's alpha (α) of 0.80 is considered an acceptable level of reliability in social science research (Krippendorff, 2012). Two professors of information systems were also assisted in checking the validity and consistency of the results.

Data Collection

Using methodological triangulation (Carter, Bryant-Lukosius, DiCenso, Blythe, & Neville, 2014), data were collected from multiple sources, including online reviews contributed and published by IoT analytics practitioners, as well as evaluation studies and enterprise surveys conducted by leading vendors of IoT analytics solutions and platforms. The online reviews used in this study were collected from Gartner.com, a leading research and advisory firm that publishes consumer-generated reviews for a wide range of enterprise IT software and services (Daradkeh, 2019b). This platform provides peer-generated online reviews with verified and reliable reviews of IoT analytics platforms and solutions published by IT and business professionals from various industries (Gartner, 2019). The resulting dataset consisted of 887 online reviews contributed by IoT specialists, data scientists and

Figure 1. Taxonomy development process (adapted from Nickerson et al. (2013) and Vaismoradi, Turunen, and Bondas (2013))



analysts, and IoT developers for ten IoT analytics platforms, including Azure IoT Analytics, AWS IoT Analytics, Oracle Stream Analytics, and Cisco Data Analytics. Although a wide range of IoT analytics platforms are available, the sample was narrowed down to the most popular IoT analytics platforms as described in Gartner’s 2019 Magic Quadrant for IoT Analytics Platforms (Gartner, 2019). Owing to their widespread popularity among practitioners and across various industries, these IoT analytics platforms had also received a relatively large number of online reviews and evaluations compared to

other platforms available in the market. In selecting IoT analytics platforms, this study considered not only their estimated annual revenue but also their placement in existing rankings by consulting and market research firms and the number of citations in academic and non-academic publications with equal weighting (see Tables 2, 3, and 4).

To supplement practitioner evaluations and online reviews, data from a variety of published use cases and associated company surveys, such as official websites, product brochures, project-related documentation, and market studies, were collected and analyzed using inductive reasoning, as recommended by Nickerson et al. (2013). A total of 113 business studies and publications were evaluated and analyzed. These publications describe the capabilities of the most widely used IoT analytics platforms from leading vendors, including Amazon, Google, Huawei, IBM, Microsoft, PTC, and SAP (see Table 5). All these publications aimed to better identify the leading IoT analytics platforms and understand the relationships between the different capabilities of IoT analytics platforms, such as IoT devices and different categories of analytics. This provided further evidence to confirm and complement practitioner evaluations and online reviews, while enabling data validation during the data analysis process (Daradkeh, 2019b)

Table 2. Selection criteria to identify the most commonly used IoT analytics platforms

Selection criteria	Sources
Number of online reviews	Online reviews from Gartner.com, written and published by IoT specialists, data scientists and analysts, as well as IoT developers from various industries, who share their perceptions and experiences with using IoT analytics platforms from major vendors such as Amazon, Google, Huawei, IBM, Microsoft, PTC and SAP (source: https://www.gartner.com/reviews/market/industrial-iot-platforms)
Annual turnover	Estimated externally generated IoT analytics Platform Revenue 2019 (MUSD) according to the market study by
Placement in rankings	Six market studies by different consulting and market research companies, which contain a total of 18 different rankings of IoT analytics platforms (see Table 3)
Number of citations	Systematic literature analysis on the state of the art of IoT analytics platforms, in which more than 150 academic and non-academic publications were evaluated and analyzed.

Table 3. Ranking of IoT analytics platforms by leading consulting and market research companies

Publisher	Title	No. of Rankings	References
IoT Analytics	IoT analytics platform comparison: how the 450 providers stack up	1	(Williams & Lueth, 2017)
Experton Group	Industrie 4.0/IoT Vendor Benchmark 2017	10	(Vogt, Landrock, & Dransfeld, 2017)
Forrester	The Forrester Wave™: Industrial IoT analytics Platforms, Q4 2019: The 14 providers that matter most and how they stack up	1	(Pelino & Miller, 2019)
Gartner	Magic Quadrant for Industrial IoT and analytics Platforms	1	(Goodness et al., 2018)
International Data Corporation (IDC)	IDC's Worldwide IoT Platforms and Analytics Taxonomy	1	(Crook & Vesset, 2020)
Pierre Audoin Consultants (PAC)	PAC RADAR IoT Platforms in Europe 2018: Vertical IoT analytics platforms are shaking up the market	7	(Vogt & Balgheim, 2018)

Table 4. Overview of the most commonly used IoT analytics platforms

Rank	IoT analytics Platform	Provider
1	Oracle IoT Cloud	Oracle
2	PTC ThingWorx	PTC
3	AWS IoT Analytics	Amazon
4	Azure IoT Analytics	Microsoft
5	SAP Leonardo IoT	SAP
6	ThingSpeak	ThingSpeak
7	SAS Analytics for IoT	SAS
8	IBM Watson IoT	IBM Corporation
9	Google Cloud IoT Analytics	Google
10	Huawei IoT Analytics Platform	Huawei Technologies Co.

Table 5. Total number of online reviews and publications collected and analyzed.

Rank	IoT Software Platform	No. of online reviews	No. of publications
1	Oracle IoT Cloud	180	7
2	PTC ThingWorx	123	16
3	AWS IoT Analytics	112	12
4	Azure IoT Analytics	99	12
5	SAP Leonardo IoT	78	12
6	ThingSpeak	72	16
7	SAS Analytics for IoT	65	12
8	IBM Watson IoT	60	15
9	Google Cloud IoT Analytics	55	6
10	Huawei IoT Analytics Platform	43	5
Total		887	113

Coding Method

Based on the research objective of this study and the IoT analytics platforms identified through the content analysis, an initial category scheme was derived from taxonomies developed in previous studies (Alkhabbas et al., 2019; Siow et al., 2018; ur Rehman et al., 2019). Based on this, previously unknown concepts were derived from the textual content in a subsequent round of inductive analysis and combined into new categories. The ending conditions for the iterative process were adopted from Nickerson et al. (2013) to ensure that the categories emerged are unique and free of overlap and that no categories were added, changed or removed in the last iteration. At the end of the analysis process, a final (revised) taxonomy is created and checked for the fulfillment of the final conditions. However, if the ending conditions are not met, a next iteration of the analysis process starts again. The theoretical saturation was already reached in the inductive process when the documents of the sixth provider were evaluated, but to ensure reliability, the documents of the seventh provider were also fully evaluated and analyzed (see Table 3). The coding process was performed throughout the entire analysis process with computer assistance using NVivo.

The coding process was then proceeded to identify the rank and frequency of capabilities of IoT analytics platforms in online reviews and other relevant publications used in this study. In a review, for example, the reviewer could refer to a particular capability several times or with different expressions. To support the calculation of the frequency intensity, NVivo was used to randomly validate the content of the data. Although NVivo has the advantage of analyzing contextual keywords from large amounts of text, it cannot replace the flexibility, intuitiveness and creativity of human coders (Daradkeh, 2019b; Daradkeh & Sabbahein, 2019). Therefore, to obtain relatively reliable results and to minimize bias, two coders were employed to manually interpret the initial results from contextualized documents. The first coder manually identified all themes and highlighted all text content describing potential capabilities of IoT analytics platforms. The second coder then manually examined the first coder's notes on the original documents. In the case of disagreement, the two coders discussed the issue and came to an agreement. After identifying all potential capabilities, the two coders then grouped them based on the context and nature of capabilities of IoT analytics platforms into two main categories: functional capabilities and cross-functional capabilities. The final agreement between the coders in this process, as measured by Krippendorff's alpha coefficient, was 82.4 percent, indicating an acceptable level of inter-rater agreement between the coders (Krippendorff, 2012). All results obtained and the agreement between coders were also validated by two professors from IS.

RESULTS

Taxonomy for IoT Analytics Platforms

Using the methodology described in the previous section, a hierarchical taxonomy was developed to uniformly describe the capabilities of IoT analytics platforms, as shown in Table 6. A distinction was made between functional capabilities that build on each other (stacked on top of each other) and cross-functional capabilities that are used across all application areas (arranged side by side and spanning the functional capabilities). The functional capabilities of IoT analytics platforms include business integration and modeling, application development, data modeling, data visualization, data analytics, data and storage management, event management, data transformation, device management, and device connectivity. Conversely, the cross-functional capabilities include information security and operations, management, and maintenance. All capabilities were ranked by frequency, with higher frequency implying higher value by both practitioners and main vendors. This taxonomy is described in more detail below based on the corresponding defined reference architecture.

Reference Architecture for IoT Analytics Platforms

To further describe the capabilities of IoT analytics platforms, the developed taxonomy was transformed into a reference architecture by mapping the previously identified capabilities to the components of an abstract software architecture, while maintaining the hierarchical arrangement according to the categorization procedure used in the research methodology. Specifically, the components of the architecture were arranged based on their content and characteristic proximity to each other and based on the flow of data and processing from an IoT device through the IoT analytics platform to other existing enterprise applications. The resulting reference architecture is shown in Figure 2 and described in detail below.

Functional Capabilities of IoT Analytics Platforms

Business Integration and Modeling

In the context of business integration and modeling, the IoT analytics platform is capable to connect the IoT devices to the existing IT infrastructure of the companies involved in the IoT use cases. In the simplest case, connectivity is established to existing EIS (enterprise information systems), whereby applications from various areas such as customer relationship management (CRM), enterprise

Table 6. A hierarchical taxonomy of the capabilities of IoT analytics platforms.

IoT analytics Capabilities	Dimensions	Characteristics	Freq.	Ranking
Functional Capabilities	Business integration and modeling		53	28
		Enterprise information system (EIS) connectors	42	35
		Business to business (B2B) communication	4	62
		Messages to make or respond to requests	31	43
	Application development		46	32
		Apps and app templates	6	60
		Model-driven development	7	59
		Visual and low-based programming	43	33
		Programming tools	49	31
		APIs and API management	85	19
	Data modeling		112	15
		Entities	199	11
		Ontologies	3	63
		Digital twins	116	14
		Mapping and matching	95	17
	Data visualization		63	23
		Metrics and KPIs	25	46
		Charts	2	64
		Maps	10	58
		Dashboard	33	37
		Repos	6	60
	Data analytics		90	18
		Descriptive analytics	22	51
		Diagnostic analytics	11	56
		Real-time analytics	29	44
		Predictive analytics	33	37
		Prescriptive analytics	18	53
		Artificial intelligence and machine learning	33	37
	Data and storage management		224	10
		Relational databases	226	9
		Non-relational databases	55	27
		Distributed ledger	27	45
		Data lake	25	46
		Object storage	40	36
		Geospatial data management	60	24

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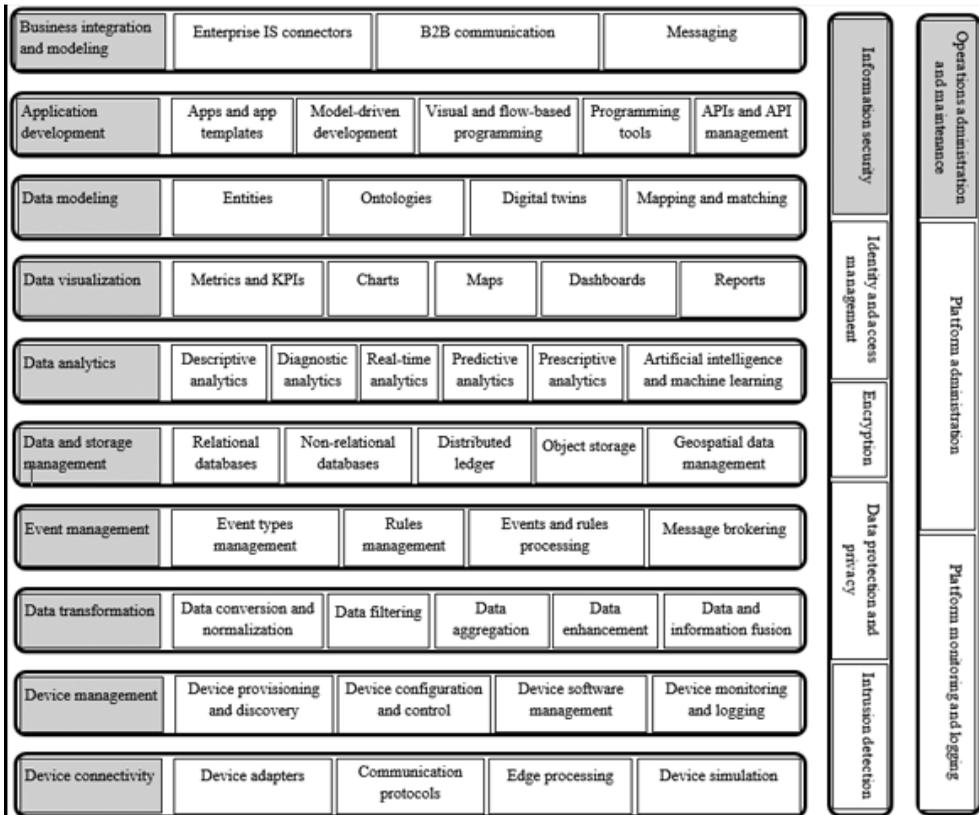
IoT analytics Capabilities	Dimensions	Characteristics	Freq.	Ranking
	Event management		229	8
		Event types management	24	48
		Rules management	66	22
		Event and rules processing	242	6
		Message brokering	242	6
	Data transformation		56	26
		Data conversion and normalization	24	48
		Data filtering	19	52
		Data aggregation	33	37
		Data enhancement	11	56
		Data and information fusion	13	55
	Device management		268	5
		Device provisioning and discovery	98	16
		Device configuration and control	60	24
		Device software management	33	37
		Device monitoring and logging	51	30
	Device connectivity		299	4
		Device adapters	43	33
		Communication protocols	306	3
		Edge processing	85	19
		Device simulation	24	48
Cross-Functional Capabilities	Information security		310	2
		Identity and access management	397	1
		Encryption	130	12
		Data protection and data privacy	122	13
		Intrusion detection system	15	54
	Operations, Administration and Maintenance		70	21
		Platform administration	33	37
		Platform monitoring and logging	53	28

resource planning (ERP), manufacturing execution system (MES) or supply chain management (SCM) are connected as required. For electronic communication across company boundaries (B2B communication), for example, different electronic data interchange (EDI) standards such as ANSI ASC X12, Electronic Business XML (ebXML), RosettaNet or UN/EDIFACT must be supported (Kulvatunyou, Oh, Ivezic, & Nieman, 2019). In addition, it is important to support different types of messaging such as e-mail or SMS for interaction between devices and enterprise applications.

Application Development

Different applications of IoT analytics have different requirements and entail different types of analytics, which should be developed as efficiently and effectively as possible. Therefore, developers are usually supported in the development of IoT analytics with pre-developed and reusable application templates (apps and app templates), programming tools such as development environments or software

Figure 2. Reference architecture for IoT analytics platforms



development kits, and suitable application programming interfaces (web service APIs) such as RESTful APIs (Ray, 2018; Sethi & Sarangi, 2017). In addition, application development can benefit from special tools that support the following types of software development:

- In model-driven development, modelling languages, modelling tools, and code generators are used to automatically generate executable software from models.
- In visual programming, visual development environments and languages are used to develop analytics applications through the arrangement and combination of graphical elements rather than through classic, text-based source code, using the drag-and-drop operating principle known in graphical user interfaces.
- In flow-based programming, where software is composed of different components using visual development environments, the components are linked together in a message-based manner.

A common feature of visual and flow-based programming is that, following the mash-up idea of Web 2.0, software development is done by combining existing content and applications from different sources via open programming interfaces.

Data Modeling

The different requirements associated with different IoT use cases also affect the area of data modeling. On the one hand, the entities to be modeled differ from application to another. On the other hand, the same entities and their properties may be modeled differently in different use cases. For example, it may be necessary to model entities such as people, systems, or machines, and the IoT devices used within an

IoT use case may represent other connected entities. Based on this, ontologies and digital twins (Boje, Guerriero, Kubicki, & Rezgui, 2020; Moder, Ehm, & Jofer, 2020) can be used for these purposes:

- An ontology is used to represent, name and define the categories and properties of, and the relationships between, objects, data and entities (Greco, Ritrovato, & Vento, 2020; Rosen, von Wichert, Lo, & Bettenhausen, 2015).
- A digital twin is used as a model of a present or future entity of the real world, which describes its properties on the basis of real data and simulates its behaviour on the basis of algorithms and simulations, thus closing the gap between the real and virtual world (Kritzinger, Karner, Traar, Henjes, & Sihm, 2018; Qi & Tao, 2018). In this context, a distinction is made between device twins for IoT devices, object twins for objects, asset twins for monitoring and production management, spatial twins as a virtual model of the physical environment of an IoT application (e.g. buildings at different locations consisting of several floors to which several rooms are assigned) and digital human twins for humans (Kritzinger et al., 2018).

In addition, data modeling must not only provide the ability to link different entities such as people, objects, rooms, or buildings, but also allow for the capture of possible changes in these relationships over time. In this context, mapping is used to manage the relationship between two entities over time, based on the identifiers of these entities. Based on this, a matching process must examine current and past relationships between entities and verify which entities are or were associated with a known ID (Tao, Zhang, Liu, & Nee, 2019).

Data Visualization

Data visualization is used to visually prepare, display, and communicate data generated by IoT devices using key performance indicators (KPIs), charts, and maps such as traffic maps, aerial imagery, and satellite imagery, which in turn can be combined and summarized in dashboards and reports, depending on the type and goal of the data to be displayed (ur Rehman et al., 2019). A dashboard has the advantage of making everything visible at a glance while providing context. In the face of upstream big data, dashboards based on IoT data provide interactive access to the organization's data and processes. This means that decision-makers and stakeholders always have the up-to-date information they need to optimally implement ideas and develop strategies on the fly or in the future.

Data Analytics

In the context of data analytics, various analysis techniques are used to generate relevant and actionable insights from the data available in a company, which also includes data collected via IoT devices, to support decision-making in the company. In the context of Industry 4.0, companies are using data analytics to make their production more efficient, further develop products and enable new analytics-based services. In particular, a distinction is made between descriptive analytics, diagnostic analytics, real-time analytics, predictive analytics, and prescriptive analytics, each of which answers different questions of increasing complexity to increase the value of the information obtained (Siow et al., 2018; ur Rehman et al., 2019). IoT solutions using descriptive analytics methods describe current machine conditions. Diagnostic analytics methods work deductively on this basis. They aggregate collected historical data with visualizations and support process optimization. Predictive methods are characterized by an inductive approach, which enables them to predict what will happen based on existing data with probabilities. Prescriptive analytics methods are the supreme discipline of data analytics today. They determine suitable solutions based on current data and taking various scenarios into account. In addition, artificial intelligence and machine learning methods are used for data analysis, where computers behave as if they had some kind of human intelligence. In particular,

machine learning methods are used to identify correlations in existing data sets with the help of learning processes and make predictions based on these findings (Adi et al., 2020).

Data and Memory Management

Data and storage management includes relational databases, non-relational databases, distributed ledgers, object storage, and spatial databases. It mainly provides create, read/retrieve, update, delete operations for both structured and unstructured data (Vongsingthong & Smachat, 2015). Depending on the IoT use case, it may be necessary to manage very large amounts of data and evaluate both current data over short periods of time as well as historical data over longer periods of time. In addition to these operations, the geospatial data management handles spatial queries, verifies spatial coordinates, and performs location searches, route planning, coordinate transformations and time zone conversions (Hu & Xu, 2019; Karkouch, Mousannif, Al Moatassime, & Noel, 2016).

Event Management

The aim of event management is to monitor business processes in real time in order to detect deviations between the planned target state and the actual state at an early stage that may have negative or positive effects. This is necessary to achieve faster response times, reduce possible consequential costs, minimize the probability of occurrence of critical events and limit negative effects through preconceived response patterns (da Cruz et al., 2018). In this context, IoT analytics platforms serve the following purposes:

- Event types management is used to classify and distinguish between events of different types, such as alarming events or confirmatory events.
- Rules management is responsible for managing business rules, which can be modeled as formal if-then constructs with multiple preconditions in the if part and defined reactions in the then part.
- In event and rule processing, status messages from IoT devices are translated into events via a target/actual comparison by evaluating business rules through rule engines.
- Message switching enables the forwarding of events in the form of messages to interested persons or IT systems via the implementation of the publish/subscribe design pattern and thus leads to a loose coupling of applications.

Data Transformation

In data transformation, data from different sources such as different IoT devices is unified and converted into a standardized data format through data conversion and data normalization. In addition, irrelevant data is reduced and condensed through data filtering and data aggregation, while different types of relevant data are combined with complementary data such as master data through data aggregation. Similar types of relevant data are also merged through data and information fusion to achieve higher data quality (Halakarnimath & Sutagundar, 2020; Karkouch et al., 2016).

Device Management

Device management is responsible for managing a large number of IoT devices (da Cruz et al., 2018) and includes the following tasks:

- Device provisioning and discovery is responsible for the description and management of IoT devices and uses, for example, reusable templates to make devices of the same type accessible and available more quickly. For further simplification, device groups can be defined if required, which can be used to transfer tasks to be performed to a large number of devices simultaneously.
- Device configuration and device control is responsible for the configuration of different properties and the transmission of commands to control IoT devices according to the specific requirements

of a specific IoT application. This includes, for example, determining the frequency within which an IoT device transmits status information.

- The device software management is responsible for the secure update of the firmware or application software on an IoT device. This usually has to be carried out and monitored via a radio-based air interface. It may also be necessary to manage different versions of a firmware or application software.
- The knowledge of current and past device states is a basic condition for the detection and correction of failure states as well as for the maintenance of the operation of IoT devices. In this context, device monitoring is used to detect and monitor the current device state, while device logging is used to create a log of device states, which can also be used to trace past changes and events.

Device Connectivity

The purpose of device connectivity is to ensure bidirectional communication between IoT devices and the IoT software platform. This involves interacting with a large number of different IoT devices that use different communication protocols (Ray, 2018). Examples of communication protocols from the IoT area are AMQP (Advanced Message Queuing Protocol), CoAP (Constrained Application Protocol) and MQTT (Message Queuing Telemetry Transport). Furthermore, for different types of IoT devices different device adapters are provided. These adapters are used to capture the IoT devices and normalize the messages exchanged over them to allow easy integration into a company's existing IT infrastructure. Depending on the IoT use case and the IoT devices used, it may also make sense to use special runtime environments for IoT devices to enable decentralized data processing at the edge of the network directly on IoT devices. Finally, a device simulation allows IoT applications to be developed and tested without connecting real IoT devices, thus accelerating development and start-up.

Cross-Functional Capabilities of IoT Analytics Platforms

Information Security

Information security must be ensured in all areas of an IoT analytics platform. As part of identity and access management, it must be ensured that access to certain IT resources and data only takes place after successful authentication of the identity of an authorized person, application or hardware component and after verification of the associated access rights through authorization (Radanliev et al., 2018). In addition, sensitive data must be protected by encryption, compliance with data protection and privacy and related privacy standards must be ensured, and possible threats and attacks must be detected and prevented with the help of an intrusion detection system (Atlam & Wills, 2020).

Operation, Management and Maintenance

The issue of operations, management and maintenance includes other capabilities that are used in all areas of an IoT analytics platform:

- Platform administration includes the configuration and maintenance of the IoT analytics platform.
- Knowing the current and past platform states is a basic requirement for detecting and correcting error conditions and maintaining the operation of an IoT analytics platform. In this context, platform monitoring is used to capture and monitor the current platform state, while platform logging is used to create a log of the platform state that can also be used to track past states and events.

Practical Application of the Reference Architecture

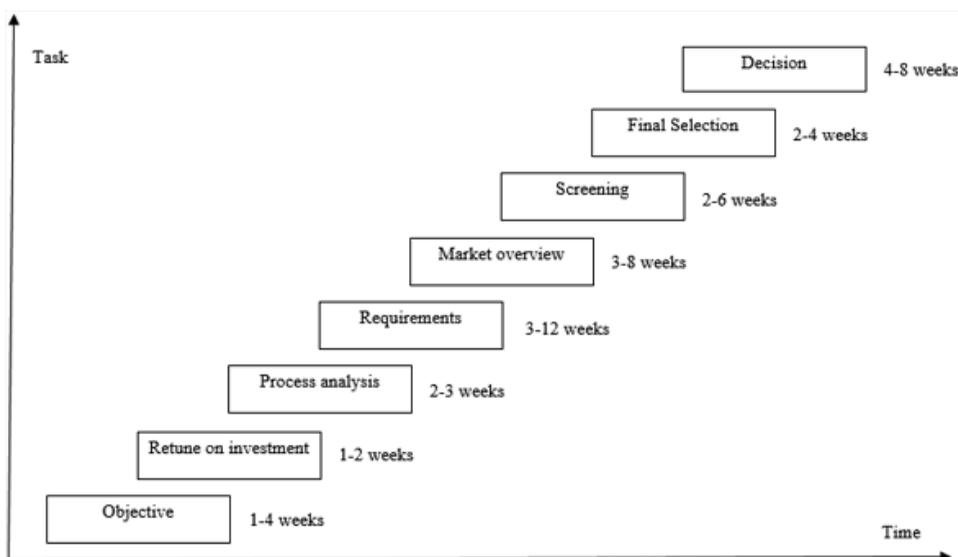
An important practical application of the reference architecture and associated taxonomy in projects is to evaluate and select the most appropriate IoT analytics platform from a set of candidates and match it with company-specific requirements.

Evaluation and Selection of Projects during the Screening Phase

In industrial standard software, endeavors aimed at evaluating and selecting the most suitable software solution from a number of candidates are typically carried out in phases lasting between 18-45 weeks or 4-10 months (Stantchev, Hoang, Schulz, & Ratchinski, 2008), depending on the application (see Figure 3). Similarly, the duration of a project to evaluate and select an IoT analytics platform from a number of candidates is estimated to be 9 months, while an associated implementation project, which includes not only the selection decision but also the integration of the IoT analytics platform and associated IoT devices into the existing infrastructure and its transition to operational use, is estimated to take 15 months (IoT Analytics, 2017).

The use of the reference architecture can be particularly useful in the screening phase described in Figure 3, which aims to filter out the relevant candidates from those previously prepared in a market study by running through various filtering steps until the remaining candidates are reduced to a manageable number. Conceivable filtering steps would be, for example, narrowing down the search to the most important providers according to the available rankings of well-known market research and consulting companies (see Table 3). Another filtering step could be based on selected knock-out criteria and the subsequent application of a multi-criteria decision-making process that evaluates and ranks the remaining candidates taking into account various relevant functional and non-functional capabilities weighted by the decision makers involved according to their requirements (Stantchev et al., 2008).

Figure 3. Phase model for the evaluation and selection of industrial standard software (adapted from Stantchev et al. (2008))



Comparison and Alignment of IoT Analytics Platforms Capabilities

In addition to the possibility of using selected capabilities from the reference architecture as knockout criteria, the reference architecture developed in this article enables the analysis and comparison of different IoT analytics platforms by providing a uniform description of their capabilities and system functionality. When evaluating and selecting the most suitable IoT analytics platform for an enterprise-specific use case, it is essential to compare the capabilities of different IoT analytics platforms while matching them with the requirements posed by a specific use case. Previous studies (see Table 1) have focused on the capabilities of different IoT analytics platforms based on reference architectures, but provide little guidance for simultaneously comparing the capabilities of different IoT analytics platforms

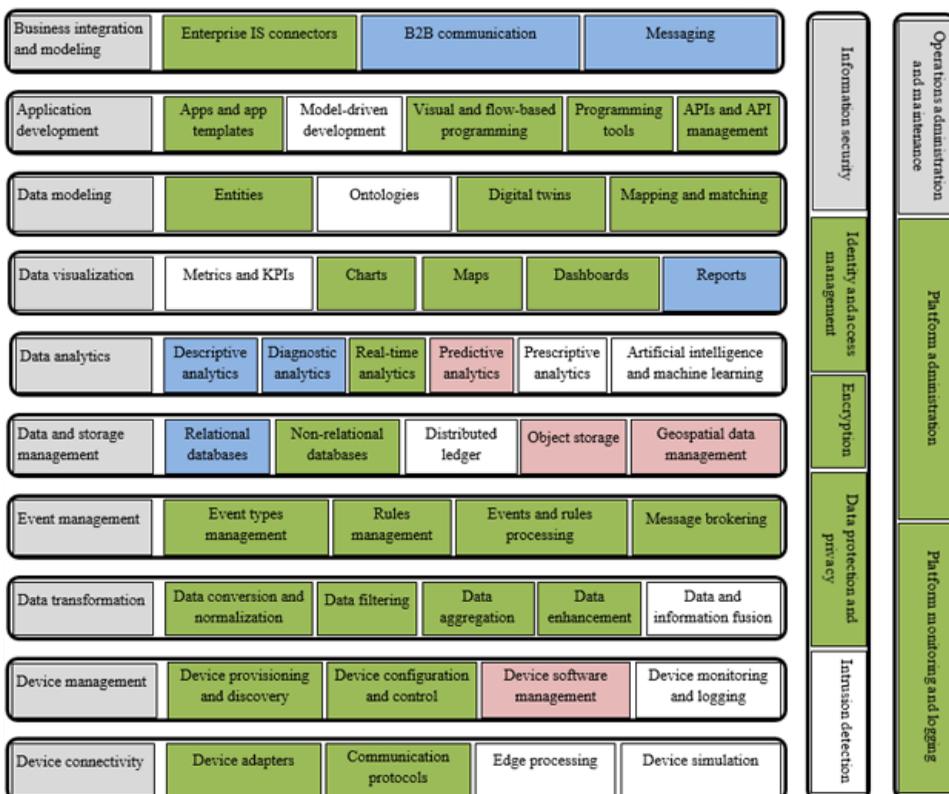
with enterprise-specific requirements. The approach proposed in this article is based on the developed reference architecture and includes both a comparison of the capabilities of different IoT analytics platforms and a comparison with the required functionality from an application and enterprise perspective.

Figure 4 describes an example scenario for a hypothetical requirements profile and a hypothetical IoT analytics platform. It shows how the reference architecture can be used to compare application-specific requirements with the capabilities supported by an IoT analytics platform by coloring each capability differently depending on whether it is required or not and whether it is supported or not. For example, the dark green color highlights capabilities that are required by the application and supported by the IoT analytics platform, while the red color highlights capabilities that are required by the application but not supported by the IoT analytics platform. When the capabilities of the various IoT analytics platforms under consideration are described in this way as part of an evaluation and selection project using the reference architecture, this uniform description leads to benchmarking of the various candidates against each other.

Evaluation and Ranking of IoT Analytics Platforms

The uniform description of the capabilities of IoT analytics platforms using the reference architecture can also be used to evaluate the functionality of different IoT analytics platforms in comparison to the functionality required by the application, thereby enabling to classify and rank the different IoT analytics platforms accordingly. For such an evaluation, the following measures are proposed, which should be calculated for each candidate:

Figure 4. Comparison of the application-specific requirements with the capabilities supported by an IoT analytics platform



- $pIoTc_p$ = Proportion of capabilities supported by the IoT analytics Platform p .
- $pReqc_p$ = Proportion of capabilities required by the application and supported by the IoT analytics Platform p .
- cos_p = Cosine similarity which measures the similarity between the application-specific capabilities required and those supported by the IoT analytics platform p .

The cosine similarity, which is widely used in information retrieval and data mining (Han, Kamber, & Pei, 2012; Sohangir & Wang, 2017), is defined as a measure of the similarity between two non-zero vectors a and b as follows:

$$\cos(a, b) = \frac{a \cdot b}{|a| \cdot |b|} = \frac{\sum_{i=1}^n a_i \cdot b_i}{\sqrt{\sum_{i=1}^n a_i^2} \cdot \sqrt{\sum_{i=1}^n b_i^2}}$$

Both the capabilities required by the application and the capabilities supported by an IoT analytics platform p can be represented as binary vectors for the calculation of cosine similarity. This representation is based on all $n \in \mathbb{N}$ capabilities contained in the reference architecture, as follows:

- Vector a for capabilities required by the application: $a = (a_1, a_2, \dots, a_n)$, with $a_i \in \{0, 1\}$ and $n \in \mathbb{N}$, where $a_i = 0$, if capability i is not required and $a_i = 1$ if capability i is required with $i \in \mathbb{N}$ and $i \leq n$.
- Vector b_p for the capabilities supported by the IoT analytics platform p : $b_p = (b_{p1}, b_{p2}, \dots, b_{pn})$ with $b_{pi} \in \{0, 1\}$ and $n \in \mathbb{N}$, where $b_{pi} = 0$ if capability i is not supported and $b_{pi} = 1$ if capability i is supported with $i \in \mathbb{N}$ and $i \leq n$.

Based on the vectors generated in this way, the cosine similarity $cos_p(a, b_p)$ is always between 0 and 1, where the value 0 is obtained for exactly oppositely directed vectors and the value 1 is obtained for exactly identically directed vectors; i.e. with maximum match between the capabilities required by the application and those supported by the IoT analytics platform p . In other words, the value 1 results exactly when the IoT analytics platform p supports exactly the capabilities required by the application. Therefore, the cosine similarity is useful for decision makers who only need a subset of all capabilities defined in the reference architecture and for whom the exact coverage of these required capabilities is more important than the proportion of total supported capabilities or the proportion of supported and required capabilities.

Based on these considerations, the illustrative example in Figure 4 shows the following ratios: $pIoTc_p = 70,6\%$, $pReqc_p = 88,2\%$ and $cos_p = 0,858$. As described earlier, during the evaluation and selection of the most suitable IoT analytics platform from a set of candidates, corresponding ratios would have to be calculated for all candidates in order to classify and rank them. Furthermore, it is worth noting that although the capabilities of an IoT analytics platform are undoubtedly an important evaluation and selection criterion, in practice other non-functional capabilities must be considered in an integrative manner in the decision-making process. Therefore, the use of a multi-criteria decision-making process that combines the key measures for the assessment of functional capabilities presented in this article with other relevant non-functional capabilities and organizational characteristics is beneficial.

DISCUSSION

The use of IoT analytics platforms has increased rapidly in various industries due to the proliferation and ubiquity of IoT devices that continuously generate huge amounts of data. However, as there is a wide range of IoT analytics platforms that offer a variety of different capabilities, companies and business decision makers face significant challenges in evaluating and selecting the best IoT analytics platform for their use cases, while maintaining a desired level of performance and functionality. Given that there is no 'one-size-fits-all' platform currently available, this research addresses this growing and important issue by developing a unified description of the most prominent capabilities of IoT analytics platforms through a taxonomy and reference architecture based on practitioners' viewpoint. Compared with other studies in the area of IoT analytics, this article leverages online reviews and relevant business and market studies of different IoT analytics platforms as its main data source. It also deals with the research problem from the perspective of a relatively large number of IoT specialists, data scientists and analysts as well as IoT developers from various industries. Thus, this article not only provides a theoretical basis for further research into the emerging problem of the evaluation, selection and adoption of IoT analytics, but also offers an actionable guidance for practical implementation.

Implications for Research

From a theoretical standpoint, this study extends prior research on IoT analytics by deriving the capabilities of IoT analytics platforms in detail with the help of a qualitative content analysis based on widely used platforms available on the market and describes them in the form of a taxonomy and reference architecture. In doing so, a distinction is made between functional capabilities that build on each other, which are arranged within the reference architecture based on their content proximity and their relationships to each other, and cross-functional capabilities that are used across all areas of an IoT analytics platforms. The taxonomy and reference architecture presented in this article can serve as a central reference source for researchers to better understand and empirically investigate the identified capabilities and their relative importance for the success of IoT analytics in organizations.

The findings from this study show that data transformation and data-related capabilities have taken a great deal of interest among practitioners in their evaluation, selection and adoption of IoT analytics platforms. Among the most important capabilities influencing practitioners in the adoption decision of IoT analytics platforms like data modeling, visualization, analytics, and management, information security and entity management are emphasized in previous studies (e.g., Adi et al., 2020; Belhadi et al., 2019; Ben-Daya et al., 2019; Côrte-Real et al., 2020; Elijah et al., 2018; Guilfoyle, 2020); indicating that these capabilities have a significant impact on the process of IoT analytics adoption. Other relevant capabilities also appeared that have not been discussed in previous studies such as device management and connectivity. In addition, the continuous development and technological advances have led to the emergence of new capabilities such as cloud services support which could not have emerged without the advent of cloud computing technology. Also, the Information security and quality of platform administration and monitoring emerged here due to the unique features of IoT analytics.

From a methodological perspective, this article demonstrates the applicability of qualitative content analysis techniques to understand the capabilities of IoT analytics platforms, which can be easily extended to other topics and technology contexts. Most previous research using qualitative methods has relied extensively on research-based tools such as surveys and focus groups to collect data on users' experiences and perceptions. In addition, the literature has mainly focused on a relatively reciprocal subset of capabilities for predicting the adoption of IoT analytics and focused on a single organization. However, in the current business ecosystem, organizations are increasingly interconnected, and users' perceptions and experiences can be affected by many factors. The unsupervised nature of online software reviews provides in-depth understanding of the diverse perceptions and usage patterns of users without the interference of solicitation. Content analysis and other text mining techniques are

powerful analytical tools to extract social and business meaning from the extensive and voluntary user data. The current article can be used as an example of a practical application of content analysis to understand practitioners' behaviors and perceptions, and addresses concerns about the declining enthusiasm for the use of qualitative content analysis in IoT analytics studies (Alvelos, Teixeira, Ramos, & Xambre, 2020; Siow et al., 2018).

Implications for Practice

The findings from this article also have practical implications for organizations seeking to promote the widespread adoption and implementation of IoT analytics platforms. They also provide a practical framework for managers not only in the early adoption, but also in the implementation and follow-up of IoT analytics applications. An exhaustive vendor search is not a practical solution for enterprises looking for a suitable IoT analytics platform. This is where companies are currently facing major challenges. In order to implement their own IoT initiatives efficiently and sustainably, it is particularly important to make the best choice of IoT analytics platform that fits their own business requirements and needs. In addition to the diversity and heterogeneity of IoT analytics platforms and their capabilities, the lack of standardized terminology and comparable information also makes it difficult to choose the right platform. This article is aimed at companies that seek to offer smart products or services to their customers using IoT and analytics solutions or expand their engagement in this area. The purpose of this article is to provide these companies with an objective insight into the most important capabilities of IoT analytics so as to make them comparable on the basis of specific categories. As such, this article can serve as an evaluation and selection tool when searching for a suitable IoT analytics platform to develop customized smart products and services. With the insights provided in this article, companies can tangibly reduce the number of vendors contacted directly, enter into detailed discussions in a much more informed manner, and overall improve the effort and chances of success in the search for a suitable IoT analytics platform.

An important criterion for the adoption of IoT analytics platforms by business decision makers is the capabilities and functional requirements supported by the platform. Potential adopters and organizations are more likely to use the platform that provides them with a full range of capabilities and functions relevant to their business needs. They are looking for IoT analytics platforms that enable them to maximize the value of the IoT data they collect, reach new customers, improve customer satisfaction, and open the door to entirely new markets. The complexity of IoT analytics platforms is also an issue for practitioners, but it is not as important as the security and capabilities of the system. Practitioners are more willing to accommodate some difficulties if the IoT analytics tool provides them with important needed analytics and reports for their work. Identifying and disseminating best practices for deploying IoT analytics technologies in operational environments can also help share and observe the value that a particular IoT analytics platform can provide.

The results presented here should be directly applicable in business use cases, as the taxonomy and associated reference architecture enable companies to align IoT analytics capabilities with business requirements in a much more systematic way. Especially in the early stages of IoT analytics development, it enables the construction of the key components of an IoT analytics ecosystem. It also helps to identify the competencies required to leverage the IoT analytics at an early stage within the company. The reference architecture presented in this article can be viewed as an effective tool during IoT analytics development to identify the strengths and weaknesses of IoT analytics platforms. It helps to evaluate which capabilities the IoT analytics platform shares with other competing platforms and which capabilities can serve as a unique selling point. In this way, differentiation potentials can be identified, and companies can drive the targeted, strategic differentiation of their own IoT analytics applications on the market.

Limitations and Future Research

The results of the present work are nevertheless subject to various limitations. It should be emphasized that the qualitative content analysis conducted is limited to the most widespread IoT analytics platforms available on the market, which were selected on the basis of the number of online reviews, estimated annual revenue, placement in existing rankings by consulting and market research companies, and the number of citations in scientific and non-scientific publications. This provides potential starting points for further research. At the same time, the iterative taxonomy development process used here allows for an extension of the presented taxonomy and the associated reference architecture. On the one hand, looking at IoT analytics platforms from niche vendors could provide further insights. On the other hand, platforms that have already been examined could be re-examined after a sufficient period of time has elapsed in order to adequately represent them even as development progresses.

Furthermore, it should be noted that the evaluation and selection of an IoT analytics platform must consider not only the functional capabilities of the platform, but also non-functional characteristics such as the vendor, available support services, associated software license, business model used, and costs associated with acquiring and operating the software (Daradkeh, 2019b). In this context, multi-criteria decision support procedures could leverage the results presented here and extend them with non-functional properties to develop a complete procedure for evaluating and selecting IoT analytics platforms.

CONCLUSION

As the IoT industry continues to proliferate and the number of connected devices grows exponentially, organizations are struggling to make sense of the wealth of data generated by connected IoT devices. In this data-rich environment, IoT analytics has emerged as a key to digital transformation, offering analytical capabilities to provide enterprises with actionable knowledge and insights for their decision-making. While previous research on IoT analytics has focused on the evaluation and selection of IoT analytics platforms, there has been limited research on IoT analytics adoption and the capabilities that are important to drive the widespread adoption of IoT analytics platforms from a practitioner perspective. In addition, previous research characterizing IoT analytics has resulted in a fragmented picture and a lack of common understanding of IoT analytics systems and their constituent parts. To address this gap, this article provides a unified description and categorization of IoT analytics capabilities through a hierarchical taxonomy and reference architecture based on a qualitative content analysis of the voice of practitioners.

The approach can be readily applied to other IoT domains, providing a systemic means to assess the growing and increasingly multidisciplinary body of knowledge. The hierarchical taxonomy and reference architecture presented in this article can serve as a theoretical foundation for future research to explore the relative importance of different capabilities to the adoption of IoT analytics technologies, and as an actionable guide for practitioners. This study is one of the few studies in organizational and management sciences that used qualitative content analysis to gain insights from a broad set of software online reviews of various IoT analytics platforms. From a theoretical perspective, this study contributes to the overall understanding of IoT analytics capabilities and the importance of aligning these capabilities with business requirements. From a methodological perspective, this study demonstrates the design, applicability, and value of inductive and deductive reasoning approaches for knowledge discovery from the textual content of online software reviews to automatically identify relevant capabilities related to IoT analytics solutions.

FUNDING AGENCY

The publisher has waived the Open Access Processing fee for this article.

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