A Taxonomy of Industrial IoT Platforms' Architectural Features

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Abstract. In the industrial Internet of Things (IIoT), the concept of digital platforms has received significant attention. Although IIoT platforms revolve around similar business objectives, they address a variety of use cases and, thus, differ considerably in their architectural setup. While research has already investigated IIoT platforms from a business or design perspective, little is known about their underlying technology stack and its implications. To unveil different IIoT platform configurations and better understand their architectural design, we systematically develop and validate a taxonomy of IIoT platforms' architectural features based on related literature, real-world cases, and expert interviews. On this foundation, we identify and discuss four IIoT platform archetypes. Our findings contribute to the descriptive knowledge in this ambiguous research field, while also elucidating the interplay of IIoT platforms' architectural setup and their purpose. From a managerial viewpoint, our results may guide practitioners in comparing and selecting a suitable IIoT platform.

Keywords: Industrial Internet of Things, IIoT Platforms, Architecture, Taxonomy, Archetypes

1 Introduction

In recent years, a large number of digital platforms emerged across industries. Digital platforms and their surrounding ecosystem form complex socio-technical systems that build on developing and managing an appropriate IT architecture and governance regime [1]. In the uprising industrial Internet of Things (IIoT), the concept of digital platforms has received significant attention, leading to the emergence of more than 620 IIoT platforms by today [2] and building a market that is growing by more than 26% a year until 2024 [3]. Such IIoT platforms provide a digital infrastructure to connect industrial devices into digital networks to collect and process the generated data and consequently facilitate data-driven services [4]. Thus, Mineraud et al. [5] define IIoT platforms as middleware systems to support and integrate heterogeneous hardware, on top of which third parties can develop complementary applications. Such applications cover manifold solutions, such as production optimization through asset monitoring and

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advising, machine health monitoring through anomaly detection, or customer transparency through better traceability.

Addressing a variety of use cases, IIoT platforms differ considerably in terms of their underlying technology stack and architectural setup [6]. This is partly due to the technical complexity in business-to-business environments and the lack of established standards in the IIoT leading to rather siloed development [6]. Consequently, the IIoT platform landscape, while revolving around similar business objectives, is scattered. On the one hand, this creates issues for companies that must understand the IIoT platform market to select a vendor that successfully integrates into their existing IT infrastructure. Companies lack a comprehensive scale to organize and guide decisions in the scattered IIoT platform landscape. On the other hand, it creates issues for researchers that seek to understand the interplay of IIoT platforms' architecture and business models, which are strongly interwoven in the context of digital technology. Research has already put effort into investigating IIoT platforms, focusing on their business model [7, 8], framework [9], or design criteria [10]. However, we still miss a unified classification of IIoT platforms' fundamental building blocks, which we subsume as architectural design options, to enable a transparent evaluation and comparison of existing IIoT platforms. Thus, we ask:

How can IIoT platforms be classified by their architectural features?

To answer this research question, we develop a taxonomy of IIoT platforms' architectural features following Nickerson et al.'s guidelines [11]. Taxonomies are well suited to lay the groundwork for emergent research fields and serve as a first step toward systematizing the fundamental design decisions [12]. For taxonomy development, we use both the literature and empirical knowledge from 22 IIoT platforms as well as seven semi-structured expert interviews. For taxonomy evaluation, we classify 50 IIoT platforms and, thus, identify and conceptualize four archetypes of IIoT platforms.

Our taxonomy contributes to the descriptive knowledge in this ambiguous research field by explaining the architectural dimensions and prevalent manifestations of digital platforms in the IIoT. Further, we contribute to the prescriptive knowledge by elucidating the interplay between IIoT platforms' architectural setup and their purpose. Lastly, our results provide a comprehensive overview of architectural dimensions that may guide practitioners in comparing and selecting a suitable IIoT platform.

2 Foundations

2.1 Digital Platforms

Originally viewed as multi-sided markets that enable interactions between different actors, the digital platform concept increasingly captured innovation activities [13]. Today, digital platforms are a pivotal element for technological innovation as the examples of Apple, Facebook, or Microsoft show [1]. Capturing this essence, Tiwana et al. [14] define digital platforms as the "extensible codebase of a software-based system that provides core functionality shared by the modules that interoperate with it and the interfaces through which they interoperate". Adding to this view, the network of third-party providers (i.e., complementors) that builds around a digital platform is often referred to as a digital platform ecosystem [15]. We adopt this view and see a digital platform as an extensible technological foundation on top of which third parties can build platform-augmenting applications. Within this view, architecture plays a significant role in the overall design of a digital platform [16]. Tiwana et al. [14] define the architecture of a digital platform as the "conceptual blueprint that describes how the ecosystem is partitioned into a relatively stable platform and a complementary set of modules that are encouraged to vary, and the design rules binding on both". Digital platforms' varying architecture makes it possible to differentiate between them and determines their evolutionary paths [14].

Digital platforms bring together three important stakeholders: the platform owner, complementors, and users. The platform owner runs and governs the digital platform. Complementors build on the digital platform and broaden its functionality with applications. The users consume the functionalities provided by the digital platform [1].

2.2 (Industrial) Internet of Things

The Internet of Things (IoT) integrates technology-enabled physical objects into a global cyber-physical network [17]. It uses recent advances in digital technology such as ubiquitous communication, pervasive computing, or ambient intelligence to connect these objects based on standardized communication protocols. With the help of these technologies, everyday objects turn into so-called smart things [18].

Prior research examines the IoT in terms of its architecture, for example, as a layered reference model [19]. This often results in a multi-layer description of services offered at different architectural levels, depending on the business needs, technical requirements, and technologies. A common three-layer IoT architecture differentiates the perception, network, and application level [20]. The perception level controls objects and collects data, the network level enables information exchange of the data, and the application level supports business services by analyzing the data.

The application of the IoT concept in an industrial context received particular interest in recent years as it proved to be a prime example of the applicability and its underlying economic potential [21]. Current trends in the manufacturing industry point towards combining traditional production, automation, and computational intelligence into a complex system known as the industrial IoT. The literature describes the IIoT concept with different names such as Industry 4.0, Industrial Internet, or Internet of Production [21, 22]. The terms IoT and IIoT are occasionally also used synonymously [4]. Sisinni et al. [19] describe it as being about "connecting all the industrial assets, including machines and control systems, with the information systems and the business processes". Thus, IIoT leverages the mechanical engineering industry into the digital era [23]. Through extraction and utilization of machine data, it is a key enabler for the creation of digital networks in manufacturing processes and ultimately lays the foundation for a smart production system [4].

2.3 Industrial Internet of Things Platforms

IIoT platforms function as a middleware that orchestrates the heterogeneous device landscape in the IIoT and provides a technological infrastructure fostering connectivity and interoperability between the smart machines, control systems, and enterprise software systems [24]. On top of the technological infrastructure, applications provide data-driven services to the platforms' users [25]. These applications consequently extend the machines' functionality by collecting and processing the generated data, thus generating additional value [4]. IIoT platforms exclusively operate in a business-to-business environment, which entails higher technological complexity due to existing hardware, IT infrastructure, and processes, compared to business-to-consumer markets in which most digital platforms operate [4].

Even though IIoT platforms operate in the same industry, they specialize in different service offerings (e.g., equipping devices with digital technology and connecting them to the internet, managing the machinery for more flexible production, or deriving findings through analyzing data). To realize these services, they require different architectural features. As a result, the IIoT platform landscape is scattered among different manifestations, making it difficult to compare IIoT platforms with each other and understand the value they can create.

Research just recently began investigating IIoT platforms, covering different aspects such as their business model [8, 26], frameworks for classification [9], or their design criteria [10]. Regarding the business model, Hodapp et al. [8] focused on constituent elements of a business model and developed a taxonomy to understand the IoT platform market. Similarly, Endres et al. [26] explored IIoT business models to identify their IIoT specific components and overall business model archetypes. One of the archetypes they identified is the 'IIoT platform business model' which is characterized by data-driven analyses through platforms and the applications on them. Regarding IIoT frameworks, Moura et al. [9] proposed a framework that is divided into layers responsible for describing and accommodating key elements for IIoT implementation in an organization. Lastly, researchers investigated how IIoT platforms can be set up by elucidating their design criteria [10] or the concept of boundary resources [24].

However, we still miss a unified classification of architectural design options to enable a transparent evaluation and comparison of existing IIoT platforms. We deem this a practical approach to uncover underlying differences of IIoT platforms that research thus far has not been able to demonstrate.

3 Method

3.1 Taxonomy Development

According to Glass and Vessey [27], taxonomy development refers to a method of "assigning members to categories in a complete and unambiguous way". Taxonomies are schemes with which specific amounts of knowledge can be structured, analyzed, and organized, thus fostering the understanding of the phenomenon [27]. Embedded in the field of design science research, taxonomies can contain both descriptive and prescriptive knowledge and represent artifacts in the form of models [11]. In information systems research, taxonomy development is well received and has already been successfully applied in different contexts when exploring emerging research fields such as smart things [18] or agile IT setups [28]. In line with this exemplary work, we follow the iterative taxonomy development method proposed by Nickerson et al. [11]. This method integrates conceptual and empirical perspectives into one comprehensive method and, thus, fosters the iterative usage of both paradigms. The method follows a seven-step-structure: (1) determination of a meta-characteristic that reflects the purpose of the taxonomy and its target group, (2) determination of ending conditions, (3) choice of either an empirical-to-conceptual (E2C) or conceptual-to-empirical (C2E) approach, (4) conceptualization of characteristics and dimensions, (5) examination of objects, (6) initial design or revision of the taxonomy, and (7) testing of ending conditions. The taxonomy's purpose is reflected in its meta-characteristic, which the researcher defines, together with ending conditions, at the beginning of the development process. Several iterations of taxonomy design and revision, choosing either a C2E or an E2C approach, follow. After each approach, the research tests the resulting taxonomy against the ending conditions until they are met.

For step (1), we define our meta-characteristic as follows: *Architectural features of IIoT platforms*. Thus, our meta-characteristic reflects that we seek to guide both further research and practitioners. For step (2), we determine objective as well as subjective ending conditions of the taxonomy development process [11]. As for the formal correctness of the taxonomy development, we test against the following objective criteria after each iteration: (I) every dimension is unique, (II) every characteristic is unique within its dimension, and (III) at least one object is classified under each characteristic of every dimension. Following Nickerson et al. [11], we define our subjective ending conditions that taxonomy development is finished after the evaluation sees it to be concise, robust, comprehensive, extensible, and explanatory. Besides, we follow Jöhnk et al. [28] and Püschel et al. [18] in combining mutually exclusive (ME) and non-exclusive (NE) dimensions to allow for a parsimonious taxonomy.

For steps (3) to (7), we alternately conducted two C2E and two E2C iterations. In the first iteration (C2E), we searched relevant literature following the guidelines of Webster and Watson [29] and vom Brocke et al. [30]. We deliberately decided to start with a C2E iteration to account for the growing amount of literature as a means to initially structure the field. Thus, we considered research on IoT, IIoT, and digital platforms to gain a comprehensive perspective on the emerging phenomenon of IIoT platforms and to populate initial dimensions and characteristics in our taxonomy. We searched the scientific databases ACM Digital Library, AIS Electronic Library, IEEE Xplore Digital Library, and SpringerLink with the following search string: TITLE("IoT platform*" OR "IIoT platform*" OR "internet of things platform*" OR "industrial internet of things platform*" OR "digital platform*") AND ABSTRACT("architecture" OR "taxonomy" OR "classification"). This search string resulted in 281 publications which we subsequently screened regarding information on architectural features of digital or (I)IoT platforms. Screening the results' titles, abstracts, and – where necessary – full-texts, we reduced the results to 91 remaining relevant publications. We used this knowledge base and additional literature from a forward- and backward search to extract and consolidate architectural features in a table. Drawing on this list in joint discussions, we developed the first increment of our taxonomy consisting of 19 dimensions and related characteristics organized in four overarching layers. Considering that the literature only rarely focuses on IIoT's specifics compared to the IoT and most architectural features in the literature revolve around security aspects, we decided to continue the taxonomy development process.

In the second iteration (E2C), we sought to back the preliminary insights with empirical evidence. Thus, we examined 22 IIoT platforms for their architectural features. We selected platforms identified through market research (e.g., from Gartner's Magic Quadrant and practitioner reports) and those mentioned in literature from the first iteration. For instance, Guth et al. [6] describe architectural features for AWS IoT and Microsoft Azure IoT Hub, among others. Thus, the descriptions and analyses from previous work helped us to confront our emerging taxonomy with existing renowned IIoT platforms. We obtained relevant information for our taxonomy development from platform providers' technical documentation, websites, whitepapers, and relevant press releases. These insights helped us to identify new architectural dimensions and characteristics as well as to substantiate and improve the existing ones. By the end of the second iteration, our taxonomy consisted of 21 dimensions organized in four layers.

In the third iteration (C2E), we returned to the literature to ground the new observations in prior work. Thereby, we strengthened and verified the findings from the second iteration. Specifically, we searched for theoretical concepts describing our observations of IIoT platforms' architectural features and dropped or consolidated dimensions and characteristics in line with our meta-characteristic. For instance, while we found information on IIoT platforms' governance in the second iteration, it does not describe their architectural features in the narrower sense, which is why we removed them from the taxonomy. The third iteration resulted in a taxonomy of 13 dimensions and related characteristics that are organized in four overarching layers.

In the fourth iteration (E2C), we collected and analyzed additional primary data from seven expert interviews (see Table 1). We deemed this iteration necessary to account for IIoT platforms' novelty and peculiarities in developing and evaluating our taxonomy. Our interviews were semi-structured, following an interview guide to ensure coverage and comparability between the interviews [31]. Each interview consisted of four building blocks: introduction (participants, research project, taxonomy research, and clarification of focal terms and concepts), discussing the layers and dimensions of the taxonomy, discussing the characteristics for each dimension in the taxonomy, and overall feedback. We selected interviewees from our industry network (convenient sampling) according to their knowledge in the field of IIoT and/or IIoT platforms. Our experts contribute perspectives from different backgrounds and industries to offset potential biases. The interviews lasted between 55 and 78 minutes and at least two of the authors were present in each interview. We recorded all interviews with the experts' consent and analyzed them systematically. Thus, all authors engaged in discussing the experts' feedback and further developing the taxonomy. We incorporated the proposed changes between interviews to discuss the improved taxonomy iteratively.

3.2 Cluster Analysis and Archetype Identification

Based on our taxonomy, we seek to identify, conceptualize, and elucidate typical architectural setups of IIoT platforms (i.e., typical combinations of architectural features). This is to understand better the current IIoT platform landscape and guide scholars as well as practitioners in this field. We identified distinct IIoT platform archetypes using cluster analysis. This statistical technique groups objects with similar characteristics and aims for a high degree of homogeneity within each cluster group and a high degree of heterogeneity between cluster groups [32].

Table 1. Overview of the seven expert interviews

	Role of interviewee	*Industry*	*Employees (2019)*	*Revenue (2019)*	*Duration*
1	Customer Engineer	Technology	119,000	141bn €	59 min.
2	Software Developer	Automotive	133,000	104bn €	58 min.
3	Emerging Tech. Specialist	Automotive	133,000	104bn €	55 min.
4	Software Architect	Software Dev.	20	1m €	58 min.
5	Head of AI/Data Analytics	Manufacturing	20,000	3.3bn €	61 min.
6	Founder/CEO	Technology	5	-	78 min.
7	Data Scientist	Automotive	90,000	55bn €	69 min.

For this step, we collected data on 50 IIoT platforms that provided the real-world cases for cluster analysis. We used the publicly accessible IIoT supplier database of the market research company IoT One to obtain a comprehensive list of relevant IIoT platforms [33]. Following a structured selection process, this platform sampling approach helped us to gain a larger number of IIoT platforms for classification compared to the taxonomy development phase. At the same time, this approach was detached from any focus and platform selection choices in previous work to increase the transparency and comprehensibility of our cluster analysis. The IoT One database contained information on 3,063 companies at the time of the data collection. We narrowed down the search results using the databases' filter options to select 'platform-as-a-service' entries, resulting in a list of 591 elements. Subsequently, we filtered the list by the five available revenue categories (<$10m, $10m-$100m, $100m-$1bn, $1bn–$10bn, >$10bn) to cover IIoT platforms of different sizes, popularity levels, and with different value propositions. We then sorted the results by profile completeness and selected the first ten platforms from each revenue category that provided sufficient documentation to classify them in our taxonomy (the selected IIoT platforms are listed in Section 5).

One author classified the selected IIoT platforms, frequently discussing ambiguities within the research team. We choose agglomerative hierarchical clustering with the Ward algorithm and Manhattan distance function as our clustering approach. We coded every characteristic as binary (1: the IIoT platform offers this architectural feature; 0: the IIoT platform does not offer this architectural feature) and normalized the dimensions' distance as [0;1] to avoid overrating dimensions with more characteristics [18]. Agglomerative hierarchical clustering shows solutions for all possible number of clusters. Thus, we used triangulation to choose the optimal number of clusters based on different statistical measures, visual graph interpretation, as well as interpretability and meaningfulness based on our real-world observations [34]. Regarding the statistical measures, both the kl-index as well as the h-index indicated four clusters as optimal. Additionally, the Dindex and the Hubert index as visual graph interpretation methods support four clusters as the optimal number of clusters as they show a significant peak in their second differences plot, which corresponds to a significant increase in the measure's value. In joint discussions with all authors, we reviewed the four cluster solution and the edge solutions (three and five clusters) to eventually decide on the final four cluster solution. Subsequently, we conceptualized the archetypes' specifics and implications.

4 Taxonomy of Architectural Setups of Industrial IoT Platforms

In the following, we present our final taxonomy (see Figure 1) and describe the dimensions and characteristics in detail. The taxonomy consists of 13 dimensions encompassing 38 characteristics that we defined according to the pre-specified meta-characteristic. To improve our taxonomy's comprehensibility and real-world fidelity, we structure the dimensions in four layers, i.e. infrastructure, network, middleware, and application layer [18].

4.1 Infrastructure Layer

Industrial IoT platforms are created and cultivated on top of digital infrastructures [35]. In the context of IIoT platforms, such digital infrastructure is represented by the smart things that are connected to the platform and the technical resources on which the platform operates. In this layer, we found three relevant dimensions.

Hardware Support. Regarding the devices that IIoT platforms allow to be connected to it, we found that some IIoT platforms constrain the connectivity to *certified hardware* (e.g., proprietary or selected third-party devices) which are approved by the platform owner, while others are *hardware-agnostic*, meaning they support any hardware as long as it fits the platforms' rough technical specifications.

Platform Hosting. Another differentiation of the infrastructure is how the IIoT platform is hosted. While defining requirements for IIoT platforms, Petrik and Herzwurm [7] name three ways of how IIoT platforms can be hosted: *on-premise*, in a *cloud*, or in a *hybrid* way using both approaches. We adopt these characteristics and extend them by differentiating between *public* and *private cloud* specifications as experts repeatedly pointed out the difference during the interviews.

Data Processing. Our taxonomy research process revealed that IIoT platforms process data on different boundaries of the platform. We found that most IIoT platforms process their data *on-platform*, meaning that depending on the level of platform hosting this happens on-premise or in the cloud. Many IIoT platforms though also offer to process data on the *edge*, meaning that processing happens in a local network or within the smart things without all generated data being sent to the IIoT platform. As some IIoT platforms offer a mixture of both approaches, we also included *fog* as a situation-based data processing characteristic.

<table>
<tr><th></th><th colspan="2">Dimension</th><th colspan="12">Characteristics</th></tr>
<tr><td rowspan="3">Infrastruc-ture Layer</td><td>Hardware Support</td><td>ME</td><td colspan="6">Certified Hardware</td><td colspan="6">Hardware-Agnostic</td></tr>
<tr><td>Platform Hosting</td><td>NE</td><td colspan="3">On-Premise</td><td colspan="3">Public Cloud</td><td colspan="3">Private Cloud</td><td colspan="3">Hybrid</td></tr>
<tr><td>Data Processing</td><td>NE</td><td colspan="4">Edge</td><td colspan="4">Fog</td><td colspan="4">On-Platform</td></tr>
<tr><td rowspan="2">Network Layer</td><td>Physical Data Transportation</td><td>NE</td><td colspan="3">Wired</td><td colspan="3">Short-Range Wireless</td><td colspan="3">Cellular</td><td colspan="3">LPWAN</td></tr>
<tr><td>Logical Data Transmission</td><td>NE</td><td colspan="4">Internet Protocols</td><td colspan="4">IoT-Specific Protocols</td><td colspan="4">Industry-Specific Protocols</td></tr>
<tr><td rowspan="5">Middleware Layer</td><td>Data Structure</td><td>NE</td><td colspan="6">Structured</td><td colspan="6">Unstructured</td></tr>
<tr><td>Analytics Types</td><td>NE</td><td colspan="3">Descriptive</td><td colspan="3">Real-Time</td><td colspan="3">Predictive</td><td colspan="3">Prescriptive</td></tr>
<tr><td>Analytics Technology</td><td>ME</td><td colspan="6">Basic</td><td colspan="6">Advanced</td></tr>
<tr><td>External Integration</td><td>NE</td><td colspan="4">Business</td><td colspan="4">Machine</td><td colspan="4">Web Services</td></tr>
<tr><td>Platform Source Code</td><td>ME</td><td colspan="4">Open Source</td><td colspan="4">Open Components</td><td colspan="4">Closed Source</td></tr>
<tr><td rowspan="3">Application Layer</td><td>APIs</td><td>ME</td><td colspan="6">Standardized APIs</td><td colspan="6">Custom APIs</td></tr>
<tr><td>Application Deployment</td><td>NE</td><td colspan="4">Platform-Native</td><td colspan="4">Containerized</td><td colspan="4">Off-Platform</td></tr>
<tr><td>Marketplace</td><td>NE</td><td colspan="4">Internal Marketplace</td><td colspan="4">External Marketplace</td><td colspan="4">No Marketplace</td></tr>
</table>

Figure 1. Taxonomy of IIoT platforms' architectural features
(ME: dimension is mutually exclusive; NE: dimension is non-exclusive)

4.2 Network Layer

As connectivity and interoperability of devices and applications are core capabilities of any IIoT platform, we defined a network layer to collect the respective dimensions. Generally, two prominent frameworks can be found in the literature to describe the structure of networks: OSI and TCP/IP model. We used these models to derive two dimensions that describe the network layer of an IIoT platform, similar to the proposed stack-lower and stack-upper layer of Sisinni et al. [19].

Physical Data Transportation. These options can be categorized into *wired*, meaning a cable-bound transmission, and wireless, therefore cable-unbound transmission. While the former represents a homogeneous group of transmission methods, the latter contains heterogeneous groupings of different wireless transmission methods. Therefore, we distinguish wireless transmission methods into three sub-categories: *short-range wireless*, which includes protocols with high performance but high power consumption and limited range (e.g., WiFi or Bluetooth), *cellular*, which have high performance, high power consumption, and long range (e.g., 5G or LTE), and *low power wide area networks (LPWAN)*, which have low performance, low power consumption and medium to high range (e.g., SigFox or LoRa).

Logical Data Transmission. Consequently, we found that IIoT platforms use different protocols to ensure a common data structure for information exchange. We distinguish between *internet protocols*, which emerged from the conventional internet (e.g., HTTP, XMPP, or Websockets), *IoT-specific protocols*, which meet specific requirements of the IoT and thus overcome many drawbacks of internet protocols (e.g., MQTT, AMQP, or CoAP), and *industry-specific protocols*, summarizing existing industry standards to connect machines (e.g., Modbus, CAN, or BACnet).

4.3 Middleware Layer

Integrating data with applications on the IIoT platform leads to different specifications, which we summarize in the middleware layer. It is responsible for the accumulation and further processing of collected data (e.g., to applications) and consists of all functionalities required by a cyber-physical system. Thus, the layer is integrating the connected hardware to the platform and the software built upon it [6].

Data Structure. When generating data in the IIoT, data can be collected and streamed in different formats and structures. Some IIoT platforms explicitly state that they can deal with *unstructured* data, while others can only process *structured* ones.

Analytics Types. Making use of generated data is a central feature of every IIoT platform. We distinguish four types of analytics methods in the domain of IIoT: *descriptive analytics*, which is the most basic form, and which analyzes historical data to reconstruct events, *real-time analytics* that focuses on current data to identify events, *predictive analytics*, which uses both historical and real-time data to predict future events, and *prescriptive analytics*, which takes the predictive approach even a step further to advise on how to deal with upcoming events.

Analytics Technology. Consequently, IIoT platforms use different kinds of technology to analyze data. We found that they can be categorized into *basic* technologies, such as statistical modeling, and *advanced* technologies such as machine learning and neural networks.

External Integration. IIoT platforms can not only analyze data collected from devices directly connected to the platforms but also include data from external sources. We found that platforms differ in their offerings to integrate other (enterprise) systems. *Business* integration includes systems that deal with business processes and data from ERP, CRM, or SCM systems, *machine* integration includes legacy systems that are used in factories such as existing PLC or SCADA systems, and *web services* integration include internet-based data sources.

Platform Source Code. The examination of exemplary IIoT platforms revealed that they leverage different approaches to further develop their software. We distinguish between *open source*, meaning that platforms provide their complete source code to the public, *open components*, meaning that platforms release single modular parts of the platform source code to the public or leverage components already being open source, and *closed source*, meaning that platforms keep their source code proprietary.

4.4 Application Layer

Based on the collected data as well as functionalities provided within the middleware layer, IIoT platforms offer the possibility of integrating applications developed internally or by third parties [1]. We summarize the architectural specifics of this provision in the application layer.

APIs. To integrate not only external systems but also applications, IIoT platforms offer different APIs. While on some platforms we only found *standardized* APIs which are maintained by the platform owner, we found other cases where platforms offered possibilities to build *custom* APIs based on predefined syntax and specifications (e.g., via an API Manager).

Application Deployment. The empirical analysis of IIoT platforms revealed that platforms use different approaches to deploy applications built internally or by third-party contributors. In most cases, applications are *platform-native*, meaning that applications have been built with tools provided by and directly running on the platform (e.g., rules engines). In other cases, we found that applications were *containerized*, meaning that the applications have been developed in an external environment, but are deployed on the platform in a containerized environment (e.g., Docker), and in few cases we found that applications were deployed *off-platform*, meaning that the applications are developed and hosted on different infrastructure (e.g., Cloud Foundry).

Marketplace. For the provision of applications to platform users, we found that IIoT platforms use different approaches. They either run an *internal marketplace*, which can be understood like an app-store on a mobile phone, or they make use of an *external marketplace*, which integrates the app-store of another digital platform (e.g., Eclipse Kura Marketplace) into the IIoT platform, or they have *no marketplace* at all.

5 Industrial IoT Platform Archetypes

Drawing on our sample of 50 IIoT platforms, we demonstrate the applicability and usefulness of our taxonomy. Thus, we first derive overarching observations on IIoT platforms' architectural features. Overall, most platforms are hardware-agnostic (82%) and hosted via a public cloud service (96%), even though many platforms offer to choose other settings (on-premise 68%, private cloud 54%, hybrid 36%) as well. While almost all IIoT platforms can process data on-platform (96%) or on the edge (72%), we found that only a minority is capable of situation-based data processing (fog 22%). Most IIoT platforms rely on wired (96%) or short-range wireless (90%) data transportation technologies (cellular 50%, LPWAN 66%). Further, they use different combinations of protocols (internet 52%, IoT-specific 40%, industry-specific 76%). Note that we only considered this characteristic as existing if the IIoT platform offered more than one protocol to account for the diversity of data transmission. Regarding data analysis, most IIoT platforms can handle structured (90%) as well as unstructured (86%) data. Further, all IIoT platforms can analyze data descriptively (100%), with that number declining, the more complex analysis gets (real-time 88%, predictive 64%, and prescriptive 22%). Accordingly, our sample shows a fair split between basic analytics technology used (44%) and advanced methods (56%) used. For external integration of data, most IIoT platforms can integrate web services (90%, business 64%, machine 48%). As for source code openness, two thirds (64%) are closed source (open source 10%, open components 26%). Further, we found a majority of IIoT platforms offering standardized APIs (82%) and deploying applications on the platform (96%) (containerized 24%, off-platform 42%). Lastly, more than half (58%) of IIoT platforms do not offer a marketplace for applications.

Based on the cluster analysis among the IIoT platforms, we identified four archetypes, which we describe hereinafter. These archetypes indicate typical combinations of IIoT platforms' architectural features. We emphasize distinctive characteristics per cluster and conceptualize the archetypes with real-world insights.

5.1 Archetype 1: Allrounders (26%)

IIoT Platforms of this archetype typically have strong markedness in many (non-exclusive) characteristics (see Figure 2). While they are strong in different platform hosting options, they also offer various network data transportation options and data transmission protocols. Further, they stand out for strong analytics capabilities and external system integration possibilities. As the only cluster, these IIoT platforms strongly leverage external innovations through open components and deploy applications through various ways on the platform, while also maintaining an internal marketplace. Allrounders are IIoT platforms that offer a full-stack solution to its users. Our data sample shows that these platforms provide comprehensive services and cover a wide range of application scenarios, ranging from device connectivity and monitoring, over data visualizations and prescriptive processes, to over-the-air updates or command execution.

<table>
<tr><th>Dimension</th><th colspan="12">Characteristics</th></tr>
<tr><td>Hardware Support</td><td colspan="6">Certified Hardware 15 %</td><td colspan="6">Hardware-Agnostic 85 %</td></tr>
<tr><td>Platform Hosting</td><td colspan="3">On-Premise 85 %</td><td colspan="3">Public Cloud 100 %</td><td colspan="3">Private Cloud 62 %</td><td colspan="3">Hybrid 70 %</td></tr>
<tr><td>Data Processing</td><td colspan="4">Edge 100 %</td><td colspan="4">Fog 15 %</td><td colspan="4">On-Platform 100 %</td></tr>
<tr><td>Physical Data Transportation</td><td colspan="3">Wired
100 %</td><td colspan="3">Short-Range Wireless
100 %</td><td colspan="3">Cellular
38 %</td><td colspan="3">LPWAN
77 %</td></tr>
<tr><td>Logical Data Transmission</td><td colspan="4">Internet Protocols
85 %</td><td colspan="4">IoT-Specific Protocols
62 %</td><td colspan="4">Industry-Specific Protocols
77 %</td></tr>
<tr><td>Data Structure</td><td colspan="6">Structured 100 %</td><td colspan="6">Unstructured 100 %</td></tr>
<tr><td>Analytics Types</td><td colspan="3">Descriptive 100 %</td><td colspan="3">Real-Time 100 %</td><td colspan="3">Predictive 100 %</td><td colspan="3">Prescriptive 69 %</td></tr>
<tr><td>Analytics Technology</td><td colspan="6">Basic 15 %</td><td colspan="6">Advanced 85 %</td></tr>
<tr><td>External Integration</td><td colspan="4">Business 85 %</td><td colspan="4">Machine 62 %</td><td colspan="4">Web Services 92 %</td></tr>
<tr><td>Platform Source Code</td><td colspan="4">Open Source 15 %</td><td colspan="4">Open Components 70 %</td><td colspan="4">Closed Source 15 %</td></tr>
<tr><td>APIs</td><td colspan="6">Standardized APIs 69 %</td><td colspan="6">Custom APIs 31 %</td></tr>
<tr><td>Application Deployment</td><td colspan="4">Platform-Native 92 %</td><td colspan="4">Containerized 85 %</td><td colspan="4">Off-Platform 69 %</td></tr>
<tr><td>Marketplace</td><td colspan="4">Internal Marketplace 69 %</td><td colspan="4">External Marketplace 0 %</td><td colspan="4">No Marketplace 31 %</td></tr>
<tr><td>Included IIoT Platforms
(In Alphabetical Order)</td><td colspan="12">AIP+, Bosch IoT Suite, GE Predix, Google IoT, IBM Watson, Informatica IoT Platform, Kaa IoT, Microsoft Azure, Onesait Platform, Oracle IoT, Redhat IoT Platform, Salesforce IoT Cloud, Siemens Mindsphere</td></tr>
<tr><td>Scale</td><td colspan="3">characteristic c ≥ 75 %</td><td colspan="3">75 % > c ≥ 50 %</td><td colspan="3">50 % > c ≥ 25 %</td><td colspan="3">c < 25 %</td></tr>
</table>

Figure 2. Characteristics of the Allrounders archetype

5.2 Archetype 2: Purists (38%)

This archetype comprises IIoT platforms that typically have strong markedness in only a few characteristics (see Figure 3). As they strongly focus on public cloud hosting, they also tend towards on-platform data processing. Further, they offer only selected data transportation options and transmission protocols. Most IIoT platforms in this cluster utilize basic analytics technology, leading to less-developed data analysis. Lastly, most platforms of this archetype do not maintain a marketplace for applications. Purist IIoT platforms are focused on a narrow use and, thus, provide only necessary functionalities. They can be extended mostly through applications that are built with platform-native tools such as rules engines or low-code/no-code development environments.

Dimension	Characteristics			
Hardware Support	Certified Hardware 16 %	Hardware-Agnostic 84 %		
Platform Hosting	On-Premise 47 %	Public Cloud 100%	Private Cloud 53 %	Hybrid 21 %
Data Processing	Edge 26 %	Fog 0 %	On-Platform 100 %	
Physical Data Transportation	Wired 89 %	Short-Range Wireless 74 %	Cellular 58 %	LPWAN 42 %
Logical Data Transmission	Internet Protocols 42 %	IoT-Specific Protocols 21 %	Industry-Specific Protocols 53 %	
Data Structure	Structured 89 %	Unstructured 74 %		
Analytics Types	Descriptive 100%	Real-Time 79 %	Predictive 37 %	Prescriptive 0 %
Analytics Technology	Basic 68 %	Advanced 32 %		
External Integration	Business 42 %	Machine 16 %	Web Services 79 %	
Platform Source Code	Open Source 11 %	Open Components 11 %	Closed Source 78 %	
APIs	Standardized APIs 89 %	Custom APIs 11 %		
Application Deployment	Platform-Native 95 %	Containerized 0%	Off-Platform 42 %	
Marketplace	Internal Marketplace 16 %	External Marketplace 11 %	No Marketplace 73 %	
Included IIoT Platforms	Aeris IoT, Asavie IoT, Ascalia IoT, AT&T M2X, Autodesk Fusion Connect, Ayla, Blackberry IoT, Blynk.io, Copa-Data Zenon, DeviceHive, EPLAN IoT, Eurotech Everyware, Exact IoT, Exosite Murano, Infor IoT, Teamviewer IoT, UBIQWEISE 2.0, Telia IoT, WolkAbout			

Figure 3. Characteristics of the Purists archetype

5.3 Archetype 3: Analysts (24%)

IIoT platforms in this cluster show strong markedness in specific characteristics (see Figure 4). They are characterized by specifications on data processing and analysis. Consequently, they focus not only on edge and on-platform but also on fog data processing. Their focus is on industry-specific protocols, while different data transportation options are offered. Regarding data analysis, these IIoT platforms provide strong analytics options, backed by advanced technologies and comprehensive integration of other company systems. Further, their source code is mostly closed, applications are deployed internally, and they don´t maintain a marketplace for applications. Analysts are IIoT platforms that place a specific focus on data-driven insights and decision-making using high-end analytics technology. A widespread use case for this archetype is the linkage of production lines and their optimization. We also found that many platforms offer their own sensors or edge devices in an as-a-service model to make better use of data-gathering.

Dimension	Characteristics			
Hardware Support	Certified Hardware 8%	Hardware-Agnostic 92%		
Platform Hosting	On-Premise 83%	Public Cloud 83%	Private Cloud 50%	Hybrid 33%
Data Processing	Edge 100%	Fog 42%	On-Platform 92%	
Physical Data Transportation	Wired 100%	Short-Range Wireless 100%	Cellular 25%	LPWAN 75%
Logical Data Transmission	Internet Protocols 16%	IoT-Specific Protocols 16%	Industry-Specific Protocols 100%	
Data Structure	Structured 83%	Unstructured 92%		
Analytics Types	Descriptive 100%	Real-Time 92%	Predictive 75%	Prescriptive 17%
Analytics Technology	Basic 17%	Advanced 83%		
External Integration	Business 58%	Machine 67%	Web Services 100%	
Platform Source Code	Open Source 0%	Open Components 17%	Closed Source 83%	
APIs	Standardized APIs 75%	Custom APIs 25%		
Application Deployment	Platform-Native 100%	Containerized 0%	Off-Platform 8%	
Marketplace	Internal Marketplace 17%	External Marketplace 0%	No Marketplace 83%	
Included IIoT Platforms	Alibaba IoT Cloud, Altair SmartWorks, Altizon, AWS IoT, Foghorn, Foghub, Hitachi Vantara Lumada, Losant, Relayr.io, SE EcoStruxure, Synap IoT, XMPro IoT			

Figure 4. Characteristics of the Analysts archetype

5.4 Archetype 4: Connectors (12%)

This archetype comprises IIoT platforms with strong markedness in the network layers' and middleware layers' characteristics (see Figure 5). These IIoT platforms are more critical regarding the connected hardware, with every second platform only supporting certified hardware. Data processing is possible in multiple ways, with a strong focus on fog processing. Data transportation possibilities and logical transmission protocols are widely offered and are supplemented by rich external system integration options. Regarding data analysis, this archetype uses basic technologies and offers only limited analytics types. Applications can be deployed either on or off the platform while using mostly a marketplace.

Connectors are IIoT platforms that specialize in integrating devices into their platforms to extract and gather data. They put stronger restrictions on hardware support or only offer standardized APIs to comply with the technological complexity and provide a reliable basis for additional contributions of platform actors. As their focus is on these topics, they rely on other services and solutions to make use of the data and provide advanced analytics tools, which other users can adopt through the marketplace.

Dimension	**Characteristics**			
Hardware Support	Certified Hardware 50%		Hardware-Agnostic 50%	
Platform Hosting	On-Premise 67%	Public Cloud 100%	Private Cloud 50%	Hybrid 17%
Data Processing	Edge 100%	Fog 67%	On-Platform 83%	
Physical Data Transportation	Wired 100%	Short-Range Wireless 100%	Cellular 100%	LPWAN 100%
Logical Data Transmission	Internet Protocols 83%	IoT-Specific Protocols 100%	Industry-Specific Protocols 100%	
Data Structure	Structured 83%		Unstructured 83%	
Analytics Types	Descriptive 100%	Real-Time 83%	Predictive 50%	Prescriptive 0%
Analytics Technology	Basic 83%		Advanced 17%	
External Integration	Business 100%	Machine 83%	Web Services 100%	
Platform Source Code	Open Source 17%	Open Components 0%	Closed Source 83%	
APIs	Standardized APIs 100%		Custom APIs 0%	
Application Deployment	Platform-Native 100%	Containerized 17%	Off-Platform 50%	
Marketplace	Internal Marketplace 83%	External Marketplace 0%	No Marketplace 17%	
Included IIoT Platforms	Cisco Jasper, Cumulocity, Itron IoT, Particle.io, PTC Thingworx, Windriver&Telit DeviceWise			

Figure 5. Characteristics of the Connectors archetype

5.5 Discussion of the Cluster Results

While exploring the four archetypes and the associated IIoT platforms in detail, we unveiled some specialties that we discuss in the following. *Allrounders* represent the most holistic archetype, characterized by an extensive list of architectural features that enable a wide range of possible application scenarios. However, this entails increased technical complexity, resulting in higher initial investment for end-users owing to the necessity of external system integrators, which are usually already partnered with Allrounders. IIoT platforms of this archetype are suitable for end-users that pursue a comprehensive approach to their IIoT strategy and require an end-to-end solution. *Purists*, in contrast, are defined by a lower technical complexity and selection of architectural features, which reduces the number of possible application scenarios but fosters a user-friendly experience and faster implementation. Thus, they are also suitable for smaller companies and applications where the available resources are scarce. Considering the different revenue categories in our data sample, we find that Allrounders are typically rather big (almost 80% of our Allrounders make at least $1bn), while Purists are rather small (start-up) IIoT platforms. This raises thrilling questions regarding IIoT platforms' evolution [36], for instance, whether Purists are a predecessor to developing into Allrounders or if they focus on specific functionalities. *Analysts* are specialized IIoT platforms focusing on advanced data analysis through high-end technology (e.g., artificial intelligence). They often rely on users to provide adequate infrastructure to enable data transmission to the platform and are, thus, particularly suitable for users that already have a multitude of data that they want to exploit. Lastly, *Connectors* focus on connecting heterogeneous devices to their IIoT platform. As they tend to have less developed analytics tools, they rely on third-party developers to provide (individual) solutions via the internal marketplace to the users. We leave it to further research to investigate how the four archetypes may complement each other and how their services can be jointly operated.

6 Conclusion and Outlook

Despite IIoT platforms' increasing importance for businesses, we still miss an understanding of different architectural setups and associated consequences of such digital platforms. Further, selecting the right IIoT platform in the heterogeneous solution landscape has become increasingly challenging for practitioners. To bridge this research gap and address the underlying practical problem, we developed a taxonomy of IIoT platforms' architectural features. In the development process, we built on empirical data from both analyzing IIoT platforms and conducting semi-structured expert interviews with practitioners involved with the IIoT, as well as conceptual data from the literature on IoT, IIoT, and digital platforms. Our final taxonomy comprises 13 dimensions organized in four layers that help researchers and practitioners to better understand this emerging phenomenon. Further, we identify and conceptualize four IIoT platform archetypes from 50 real-world cases that help us to systematize the IIoT platform landscape and add an architectural perspective to recent discourse.

Thus, our theoretical contribution is threefold. First, our taxonomy adds to the descriptive knowledge in this relatively young research field by structuring and explaining what architectural features constitute prevalent manifestations of IIoT platforms. Thereby, we follow de Reuver et al.'s [15] recommendation to foster the development of contextualized theories on digital platforms as well as to conduct data-driven research. Second, we offer researchers and practitioners a mutual nomenclature that specifies IIoT platforms' architectural features. With this, we extend current research, which is largely limited to rather simple category lists built through vague development processes. Third, we elucidate typical architectural setups of IIoT platforms and how this shapes their business logic. We see this as the necessary foundations to better understand the reciprocal interplay of both aspects, i.e. how architectural design options enable IIoT platform business models and vice versa. From a managerial perspective, our taxonomy and the four archetypes help practitioners in comparing different IIoT platform solutions and enable them to select the one that not only fits the existing IT infrastructure but also provides desired solution capabilities.

We acknowledge some limitations in our research that open promising avenues for further research. Our taxonomy rests on the data used and the sequence of iterations. Although our dataset covers a fair amount of IIoT platforms of different sizes and with different foci in terms of their value proposition, we might have missed some instantiations. Future research may incorporate additional IIoT platforms and conduct further iterations to validate and update our proposed taxonomy and the resulting archetypes. Further, we did not address potential dependencies between dimensions and characteristics or the architectural success criteria of IIoT platforms. Investigating these aspects may help in the successful design and use of IIoT platforms. Lastly, future research may test our archetypes' external validity to ensure their generalizability and to explore their evolutionary paths (e.g., IIoT platform sizes within and across clusters).

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