Unblackboxing Smart Things - A Multi-Layer Taxonomy and Clusters of Non-Technical Smart Thing Characteristics

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Abstract

The Internet of Things (IoT), which describes the equipment of physical objects with sensors, actuators, computing logic, and connectivity, has attracted much attention. Although many facets of the IoT have already been explored, existing works either treat smart things as black box or focus on their technical characteristics. From an engineering management perspective, however, also a profound understanding of non-technical smart thing characteristics is key. Hence, we developed and evaluated a corresponding multi-layer taxonomy based on the latest IoT literature and a deliberately broad sample of 200 smart things, which covers the diversity of smart things available on the market. Based on eleven dimensions, the taxonomy enables classifying smart things according to the layers of established IoT architectures. Based on our sample, we inferred five clusters, each covering a typical combination of non-technical smart thing characteristics occurring in practice. These results extend our understanding of the IoT by structuring non-technical characteristics of smart things and by abstracting the diversity of smart things into artefacts with manageable complexity. Our results inspire future research on the adoption, affordances, and design of smart things. Moreover, engineering managers can use our results in early phases of product development and process reengineering projects.

Keywords: Internet of Things, Digitalization, Smart Thing, Taxonomy, Cluster Analysis

1 Introduction

The emergence of digital technologies such as Social, Mobile, Analytics, and Cloud has entailed changes for individuals, organizations, and society [1, 2]. Among the technologies that have attracted much attention in recent years is the Internet of Things (IoT), which describes the equipment of physical objects with sensors, actuators, computing logic, and connectivity [3, 4]. These technology-equipped physical objects, also referred to as *smart things*, are the nucleus of the IoT and build the foundation for applications in diverse domains [2].

Consulting and market research organizations attribute huge potential to the IoT. Market spend amounted to USD 690 billion in 2015 and is expected to reach USD 11.3 trillion in 2025 [5, 6]. Reportedly, 130 devices are connected to the Internet every second [7]. For five years in a row, the IoT has been a dominant trend in the Gartner Hype Cycle [8, 9]. The International Telecommunication Union even expressed the vision that "from *anytime, anyplace* connectivity for *anyone,* we will now have connectivity for *anything*" [10, p. 2]. Moreover, the IoT is not limited to individual smart things but enables broader contexts such as product systems with interacting smart things and IoT ecosystems that coordinate product systems [4].

Multiple facets of the IoT have already been studied [11–13]. LaBuda and Gillespie [14], for instance, focus on technical challenges such as security, interoperability, and data processing. From a business-to-business (B2B) perspective, logistics and supply chain cases have been analyzed [15, 16]. From a business-to-consumer (B2C) perspective, Dijkman *et al.* [17] and Turber *et al.* [18] discuss IoT-enabled business models, Oberländer *et al.* [3] pose that smart things evolve into autonomous actors, and Beverungen *et al.* [19] conceptualize smart things as boundary objects. Other works examine how the IoT influences user experience [20] or enhances data quality [21]. Their merits being undisputed, all these works treat smart things as black box, disregarding that their characteristics determine how individuals can use smart things and how companies can incorporate them in their value propositions.

Although they do not treat smart things as black box, Barker *et al.* [22], Dorsemaine *et al.* [23], López *et al.* [24] and Mountrouidou *et al.* [25] focus on the technical characteristics of smart things (e.g., operating system). For the purposes of engineering management, an understanding of both technical and non-technical characteristics is key. So far, only Püschel *et al.* [26] investigated non-technical smart thing characteristics (e.g., interaction partners). Their work, however, only builds on a small sample and, published several years ago, does not reflect the latest developments in the fast-evolving IoT literature and market. Hence, our research question is: *What non-technical characteristics can be used to distinguish smart things?*

To answer this question, we analyzed smart things on two granularity levels. On a fine-grained level, we developed a taxonomy for classifying smart things via dimensions and non-technical characteristics structured according to the layers of established IoT architectures, which range from the physical product to digital services. To build and validate the taxonomy, we applied Nickerson *et al.*'s [27] established taxonomy development method. Moreover, we used a sample of 200 smart things and reviewed the latest IoT literature. The sample deliberately included smart things from diverse IoT application domains to cover the full range of smart things and to increase the applicability of our results. On a coarse-grained level, we applied cluster analysis to inductively infer smart thing clusters from our sample, each covering a typical combination of non-technical characteristics, to abstract from the combinatorial diversity of smart things and to gain high-level insights into smart things available on the market.

Our study is structured as follows: In section 2, we provide domain background on the IoT. In section 3, we outline our research method. In sections 4 and 5, we present our results. Our study concludes in section 6 with implications, followed by a discussion of limitations and an outlook.

2 Background

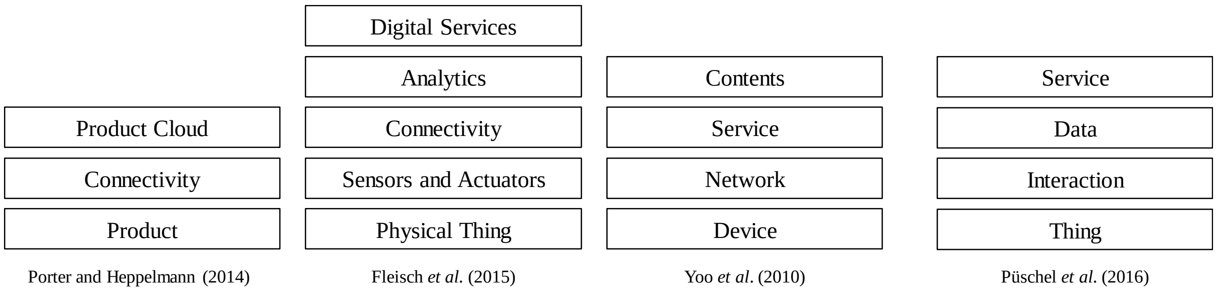
Smart things relate to the third wave of IT [4]. The first wave brought process automation, which increased productivity through automated data collection, processing, and analysis [28]. Characterized by the uptake of the Internet, the second wave enabled new levels of connectivity with free data exchange. In the third wave, IT is embedded into products through sensors, actuators, computing components, and connectivity [29]. This is characteristic of pervasive digital technologies in general and the IoT in particular [4, 30].

For some time, there was no common understanding of the term *Internet of Things* [2, 11, 31]. One reason was that the term has been used to convey different conceptualizations of two dimensions: the communication and the thing dimension. As for communication, it was not clear whether wired networks were included [32]. The same holds for the thing dimension regarding the inclusion of devices such as personal computers (PCs), smartphones, or tablets and whether smart things may only feature a digital representation [2, 3, 11]. In recent works, the IoT is defined as the connectivity of physical objects, equipped with sensors, actuators, and computing logic, with the Internet through communication technology [3]. Wired and wireless communication is covered [32, 33]. Moreover, smart things should exist independently from IT [34, 35], which is why PCs, smartphones, and tablets serve as intermediaries between humans and smart things [32]. Finally, physical materiality and a digital representation are required [19, 36].

The latest generations of smart things can act independently from human agency in ever more scenarios [4, 37]. Oberländer *et al.* [3] pose that the IoT enables a new perspective on material agency, which has been defined as the way objects act when humans provoke it [37, 38]. This understanding should be updated, as the IoT empowers smart things to act and make decisions independently of human agency. This capability, also referred to as autonomy or self-dependency, uses self-x (e.g., self-monitoring, -diagnosis, -configuration, -learning) and extended data analysis capabilities (e.g., predictive and prescriptive analytics) [4, 39, 40].

When IoT solutions are implemented, architecture models known as IoT (technology) architectures have emerged. Figure 1 provides an overview of existing architectures. Popular examples ranging from the physical product to digital services are the works of Porter and Heppelmann [4], Fleisch *et al.* [41], and Yoo *et al.* [42]. As the layers of these architectures largely overlap, Püschel *et al.* [26] compiled an integrated architecture including a *thing*, an *interaction*, a *data*, and a *service* layer. The thing layer relates to the physical thing equipped with sensors, actuators, and computing logic. The interaction layer covers the ability of physical things to interact with and be remotely accessed by other entities. The data layer covers data sources and usage. The service layer investigates the value proposition of smart things and their role in broader contexts such as IoT ecosystems. As our work builds on and extends Püschel *et al.* [26], we used their integrated IoT architecture for grouping the dimensions included in our taxonomy.

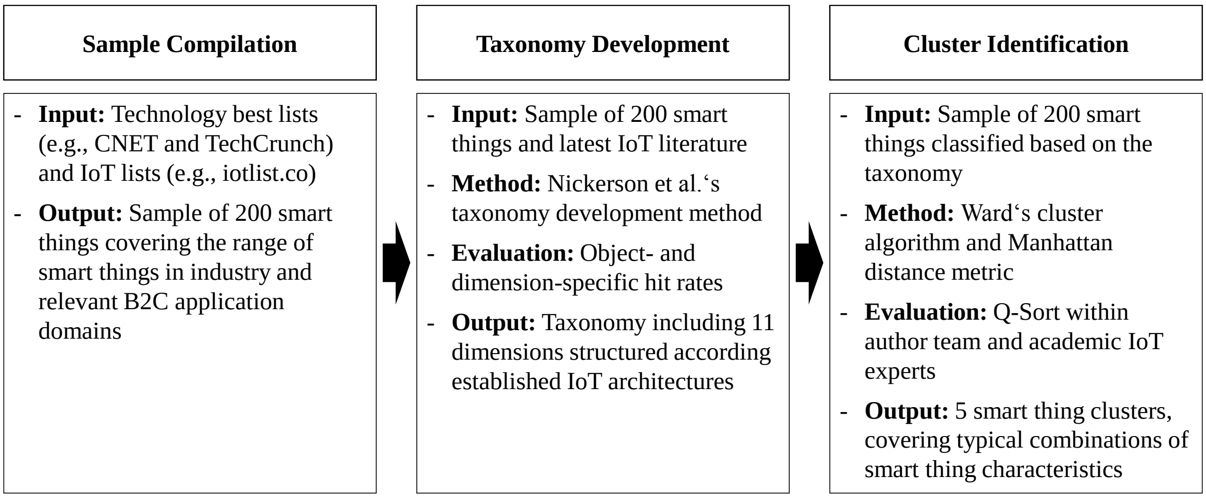
Figure 1: Popular IoT Architectures from the Literature (Simplified Illustration)



3 Research Method

To answer our research question, we first developed a taxonomy of smart things with a focus on non-technical characteristics and then inferred clusters representing typical combinations of these characteristics. The taxonomy and the clusters build on a sample of smart things compiled from diverse IoT domains [2]. Figure 2 provides an overview of our research process, before we present details in the following sections. As we compiled the sample during the development of the taxonomy, we present details when outlining how we developed the taxonomy.

Figure 2: Research Process



3.1 Development of a Taxonomy of Smart Things

We first developed a taxonomy of smart things in line with Nickerson *et al.* [27], who proposed one of the most established taxonomy development methods [43]. Often used synonymously with terms such as framework or typology, taxonomies are empirically and/or conceptually derived groupings in terms of dimensions and characteristics. Whereas, from a theory-building perspective, taxonomies represent theories for analyzing [44], they can also be understood as design artifacts enabling the classification of existing and future objects [27]. Taxonomies represent an 'organizational systematics' approach, which is crucial for sound scientific method and theoretical advancements [45, 46].

Nickerson *et al.*'s [27] taxonomy development method includes the following steps: determination of a meta-characteristic, determination of objective and subjective ending conditions, iterative choice of approach, design or revision of the taxonomy, and testing of ending conditions. The meta-characteristic is the basis from which all other characteristics are derived, reflecting the purpose of a taxonomy. As for the choice of approach, Nickerson *et al.* [27] propose an empirical-to-conceptual and a conceptual-to-empirical approach. In the empirical-to-conceptual approach, real-life objects are selected, characteristics are induced, given conceptual labels, and assigned to dimensions. In the conceptual-to-empirical approach, researchers first propose dimensions and characteristics, before dimensions and characteristics are examined by classifying objects. This leads to an initial or revised taxonomy. Both approaches are iterated as required until all ending conditions are met.

In line with our research question, our meta-characteristic was *characteristics of smart things structured according to the layers of IoT architectures.* We used the layers of established IoT architectures to group dimensions in order to increase the taxonomy's understandability and to cover relevant non-technical perspectives on smart things. We used the objective ending conditions proposed by Nickerson *et al.* [27]: every characteristic is unique in its dimension, every dimension is unique and not repeated, at least one object is classified under each characteristic of each dimension, and no new dimensions or characteristics have been added in the last iteration. Regarding subjective ending conditions, the taxonomy development process terminated after all co-authors agreed that the taxonomy was concise, robust, comprehensive, explanatory, and extendible. Below, we provide details on all iterations and on how we compiled our sample of 200 smart things (Table 1).

Iteration 1: In the first iteration, we chose the conceptual-to-empirical approach to conceptualize dimensions and characteristics based on the latest IoT literature. With Nickerson *et al.* [27] recommending to build on existing taxonomies, we used Püschel *et al.*'s [26] work as a starting point as they were the only to propose a taxonomy with non-technical smart things characteristics. To challenge the initial taxonomy, we used the latest versions of those 50 things Püschel *et al.* [26] had compiled through a literature review and a search in the Crunch Base database.

Table 1: Iterations of the Taxonomy Development Process

# It	Approach	Changes	Ending conditions	Real-life objects
1	Conceptual-to-empirical	- Addition of the dimension *autonomy* to the *thing layer* (based on the literature) - Addition of the *human-computer interaction* to the *interaction layer* (based on literature) - Removal of the dimension *human-computer interaction* based on object classification	*x* Objective conditions violated: - Empty characteristic (i.e., *human-computer interaction*) as the type of interaction (e.g., mechanical or acoustic) described the smart thing for the intended users in too much detail	50 (updated) real-life examples as used by Püschel *et al.* [26]
		- Update of the definitions of the *sensing capabilities* dimension in line with Daft and Engel [49]	*x* Subjective conditions violated: - Not explanatory as the former definition described that smart things collect little or huge amounts of data which did not allow for to comparing smart things	
		- Addition of the dimension *ecosystem integration* to the service layer and removal of the dimension *thing compatibility*	*x* Objective conditions violated: - Redundancy regarding duplication of the dimensions *ecosystem integration* and *thing compatibility*	
2	Empirical-to-conceptual	- Removal of the characteristic *many-to-many* of the dimension *multiplicity*	*x* Objective conditions violated: - Empty characteristic as the taxonomy focuses on single smart thing	Additional 75 smart things identified from recent best lists in technology news web sources (e.g., CNET and TechCrunch) and from publicly updated IoT lists (e.g., iotlist.co and smarthomedb.com). Overall sample: 125 smart things
		- Switch of the two characteristics *limited* and *none* of the dimension *offline functionality*	*x* Subjective conditions violated: - Not concise/useful as smart things could not be classified intuitively as we classify smart things along the dimensions' scale (i.e., ordinal scale)	
		- Renaming of the dimension *main purpose* to *value proposition* and emphasize the differentiation of the characteristics *thing-centric* and *service-centric*	*x* Subjective conditions violated: - Not explanatory as smart things are defined by the provided value which can be primarily physical (i.e., thing-centric) or digital (i.e., service-centric)	
3	Empirical-to-conceptual	- Final fine-tuning of labels of characteristics to enable unambiguous and intuitive classification	✓ All objective and subjective conditions met: Every dimension is unique and not repeated, at least one object can be classified under each characteristic of each dimension. All authors agreed that the taxonomy was concise, robust, comprehensive, extendible, and explanatory	Additional 75 smart things identified from recent best lists in technology news web sources (e.g., CNET and TechCrunch) and from publicly updated IoT lists (e.g., iotlist.co and smarthomedb.com). Overall sample of 200 smart things

Iteration 2 and 3: In the next iterations, we applied the empirical-to-conceptual approach. This allowed for considering the latest developments in the market. In both iterations, we used additional 75 smart things to infer new characteristics based on recent lists from technology web sources (i.e., CNET, TechCrunch, and ECT News Network's TechNewsWorld). We also added smart things from publicly updated IoT lists (e.g., iotlist.co and smarthomedb.com). Thereby, we aimed for a highly diverse sample that covers the full range of smart things available on the market and relevant IoT application domains to support the applicability of the taxonomy [2]. Thereby, we restricted our sample to the B2C domain as much more information about smart things is publicly available [3]. We get back to this limitation in Section 6.

Table 2: Sample Overview

Application Domain (according to [2])	Fraction
Smart Home	49%
Smart Health	17%
Smart Energy	9%
Individual Well-Being	21%
Smart Mobility	3%
Smart City	2%

Cluster (based on our cluster analysis, see Appendix 3 for details)	Fraction
Standalone Thing-Centric Executant	19%
Connected Thing-Centric Performer	20%
Standalone Service-Centric Monitor	26%
Connected Service-Centric Partner	15%
Self-Learning Service-Centric All-rounder	20%

After all ending conditions had been met (Table 1), two co-authors evaluated the taxonomy by independently classifying the sample (Appendix 2) based on public information (Appendix 1). Agreement was measured in terms of hit rates [47, 48]. As for dimensions with non-exclusive characteristics, i.e., an individual smart thing can feature more characteristics of one dimension, we also accounted for partial agreement to weigh all dimensions equally.

3.2 Identification of Smart Thing Clusters

Based on our taxonomy, we aimed at understanding on a more coarse-grained level which non-technical smart thing characteristics typically occur together, as the taxonomy offers 272,160 possibilities for classifying smart things[1]. While such a high granularity supports product development by structuring the design space used for ideation, it is too detailed for managerial purposes. Hence, we set out to identify clusters by applying cluster analysis to the sample of 200 smart things according to the taxonomy.

Cluster analysis is a statistical data analysis technique that groups objects according to their similarity [50, 51]. The literature offers various cluster algorithms, with the separation into hierarchical and partitioning algorithms being most common one [52, 53]. Partitioning algorithms use a given number of clusters, followed by an iterative re-assignment of objects. Hierarchical algorithms either group objects according to their similarity in an agglomerative way starting with as many clusters as objects or they divide clusters starting with one cluster including all objects [54]. We used Ward's [55] agglomerative algorithm [56, 57] and the Manhattan metric as distance measure, as both have proven useful in combination and fit our data [58].

Based on the taxonomy, we considered three variable types: (1) dimensions with nominal and mutually exclusive characteristics, (2) dimensions with nominal and non-exclusive characteristics, and (3) dimensions with ordinal and mutually exclusive characteristics. To treat all dimensions equally, we normalized the maximum distance of two smart things to 1 per dimension. As for the first two variable types, we used Bacher *et al.*'s [59] approach to encoding nominal binary variables, using one binary variable per characteristic. As for the third type, we used quasi-metric scaling based on numbers ranging from 0 to 1 [60, 61].

After that, we determined the appropriate number of clusters, a decision that required a joint quantitative and qualitative justification [62]. To get a feeling about the number of clusters, we

[1] The number of possible realizations can be calculated as follows: For dimensions with mutually exclusive characteristics, the number of characteristics is considered. For dimensions with non-exclusive characteristics, the cardinality of the characteristics' power set minus 1 is considered. Finally, all dimension-specific parameters must be multiplied, leading to the following possible number of realizations: $= 3 \cdot 2 \cdot 2 \cdot 3 \cdot (2^4-1) \cdot (2^3-1) \cdot 2 \cdot 2 \cdot 3 \cdot (2^2-1) \cdot 2 = 272{,}160$

started by analyzing the error sum of squares (ESS) [55, 63], the majority rule for twenty common indices [64], and two graphical indices [64]. The ESS suggested using three clusters. The CH [65] and the Duda index [66], which performed best in a simulation study by Milligan and Cooper [67], suggested using two and 12 clusters, respectively. Another 18 relevant indices returned between one and 15 clusters, and the majority rule recommended using three clusters [64]. As for the graphical indices, the Hubert index suggested five clusters, while the Dindex suggested three and five clusters. Hence, we concluded that the appropriate solution was likely to have between three to five clusters. Subsequently, we interpreted the solutions with three, four, and five clusters – and that with six clusters to offset potential bias. In the solutions with three and four clusters, valuable information was lost (e.g., autonomy and ecosystem integration). In the six-cluster solution, one cluster with 15 smart things was separated from another with 51 smart things. As the new cluster only had one constitutive characteristic, we dropped this solution. Finally, we chose five cluster solution, as each cluster could be reasonably interpreted standalone and in relation to the other clusters. We provide more details in Section 5.

To evaluate the clusters and their names determined within the author team, we applied the Q-sort, a statistical approach used to classify items (i.e., smart things as Q-set) in accordance with predefined constructs (i.e., the clusters) by two or more judges (P-set). Developed to examine people's attitudes and opinions [68], the Q-sort has been applied in marketing, psychology, and sociology [69] and to evaluate taxonomies [3, 70]. The judges' agreement forms the basis for assessing reliability and validity [48]. We measured reliability via the Kappa Coefficient, defined as "the proportion of joint judgment in which there is agreement after chance agreement is excluded" [48, p. 115]. While Cohen's Kappa [71] accounts for two judges, Fleiss' Kappa deals with more than two judges [72]. Validity was measured as recommended via hit rates, i.e., the frequency at which items are correctly assigned. Table 3 summarizes the theoretical background of the Q-Sort approach.

Table 3: Evaluation Criteria for Two Rounds of the Q-Sort

	Scenario 1	**Scenario 2**
P-set	2 co-authors	15 academics with an IoT background
Q-set	20 smart things	20 smart things
Construct validity measure	Hit ratio	Hit ratio
Reliability measure	Cohen's Kappa coefficient	Fleiss' Kappa coefficient

When applying the Q-sort, judges require a detailed understanding and should not be selected randomly [73]. Hence, we involved participants with an IoT background. As for the Q-set, we selected 20 smart things, at least three per cluster. We also selected at least two smart things per application domain (i.e., Smart Home, Smart Health, Smart Energy, and Individual Well-Being). In a first scenario, two co-authors yet unfamiliar with the clusters classified the Q-set. In a second scenario, 15 academics with an IoT background did the same. For both scenarios, we calculated reliability and validity. Details can be found in Appendix 3 and the results of the Q-Sort in Section 5.

4 A Multi-Layer Taxonomy of Smart Things

We now present our taxonomy, which comprises four layers according to established IoT architectures (Section 2) and eleven dimensions grouped according to these layers. Table 4 shows the taxonomy and compiles relevant definitions. Below, we present each layer in detail. Starting with a short description per layer, we present all related dimensions and characteristics using justificatory references and real-world examples from our sample.

4.1 Thing Layer

The thing layer is the foundation for all other layers [4]. Here, physical things are transformed into smart things by being equipped with *sensing* and *acting capabilities* [2]. The thing layer also covers the *autonomy* of smart things [74].

Table 4: Multi-layer Taxonomy of Smart Things

	Dimension	Characteristics				Scale	Exclusivity
Service	**Ecosystem Integration**	None	Proprietary		Open	Ordinal	ME
Service	**Value Proposition**	Thing-centric		Service-centric		Nominal	ME
Service	**Offline Functionality**	None		Limited		Nominal	ME
Data	**Data Usage**	Transactional	Analytical (basic)		Analytical (extended)	Ordinal	ME
Data	**Data Source**	Thing State	Thing Context	Thing Usage	Cloud	Nominal	NE
Interaction	**Interaction Partner**	User(s)	Business(es)		Thing(s)	Nominal	NE
Interaction	**Interaction Multiplicity**	One-to-one		One-to-many		Nominal	ME
Interaction	**Interaction Direction**	Unidirectional		Bi-directional		Nominal	ME
Thing	**Autonomy**	None	Self-Controlled		Self-Learning	Ordinal	ME
Thing	**Acting Capabilities**	Own		Intermediary		Nominal	NE
Thing	**Sensing Capabilities**	Lean		Rich		Ordinal	ME

ME: Mutually exclusive NE: Non-exclusive

Sensing Capabilities: The collection of data about the physical environment (e.g., temperature, humidity, or brightness) is constitutive of smart things [2]. Different technologies are available to implement sensing capabilities [11]. Appelboom *et al.* [75] provide an extensive overview of sensor types and related technologies. For our purposes, we take an information processing perspective in line with media richness theory [49]. With information richness being defined as the ability of information to change understanding, we focus on what smart things can collect and deliberately abstract from technical details. We also abstract from the sheer quantity of sensors implemented in a smart thing. Rather, we focus on whether a smart thing has *lean* or *rich* sensing capabilities. Smart things feature lean sensing capabilities, if they collect simple data, e.g., the smart shower Eva Drop equipped with position and temperature sensors. Rich sensing capabilities are found in smart things that collect complex data, such as the smart security camera Nest Cam IQ that uses 4K-colour and sub-sound sensors.

Table 5: Definitions and Justificatory References

Dimension	Definitions	Justificatory References
Ecosystem Integration	**None:** There is no possibility to integrate the smart thing into ecosystems. **Proprietary:** The smart thing can be integrated into ecosystems but is only compatible with smart things of the same provider or manufacturer. **Open:** The smart thing can be integrated into different ecosystems, as it is compatible with smart things of other providers and manufacturers.	[4, 32, 40, 41, 76]
Value Proposition	**Thing-centric:** The smart thing primarily serves a thing-related purpose. **Service-centric:** The smart thing serves as distribution mechanism for digital services.	
Offline Functionality	**None:** The smart thing provides no functionality without Internet connection. **Limited:** The smart thing provides parts of its functionality without Internet connection.	
Data Usage	**Transactional:** The smart thing processes data of transactions or interactions. **Analytical (basic):** The smart thing processes data for descriptive purposes. **Analytical (extended):** The smart thing processes data for diagnostic, predictive, or prescriptive purposes.	[2, 12, 16, 40, 74, 77, 78]
Data Source	**Thing state:** The smart thing processes data about its internal condition. **Thing context:** The smart thing processes data about its physical environment. **Thing usage:** The smart thing processes data about its usage. **Cloud:** The smart thing processes external data primarily from the cloud.	
Interaction Partner	**User(s):** The smart thing interacts with human users. **Business(es):** The smart thing interacts with businesses. **Thing(s):** The smart thing interacts with other smart things.	[3, 4, 40, 41, 79, 80]
Interaction Multiplicity	**One-to-one:** The smart thing interacts with a single interaction partner. **One-to-many:** The smart thing interacts with many interaction partners.	
Interaction Direction	**Unidirectional:** Data flows in one direction. **Bidirectional:** Data flows in all directions.	
Autonomy	**None:** The smart thing cannot learn and needs an external trigger for any action. **Self-controlled:** The smart thing cannot learn but operates in an independent manner without external intervention to fulfil specific tasks. It needs external triggers. **Self-learning:** The smart thing can act and decide in line with goals and improves over time by learning. It takes over decision-making tasks and adapt to a user's needs and preferences. The smart thing acts without external intervention and does not require external triggers.	[2, 4, 19, 32, 39, 42, 49, 74]
Acting Capabilities	**Own:** The smart thing directly interacts with the environment. **Intermediary:** The smart thing relies on intermediaries to interact with the environment.	
Sensing Capabilities	**Lean:** The smart thing collects simple data. **Rich:** The smart thing collects complex data.	

Acting Capabilities: In addition to collecting data from the environment through sensors, smart things can influence their environment through actuators [19]. We conceptualize acting capabilities by examining how smart things influence their environment (e.g., via audible signals, text, or voice messages). In contrast to the interaction layer, this dimension primarily focuses on a smart thing's local level. As for the characteristics of this dimension, we distinguish between smart things with *own* acting capabilities (e.g., the activity tracker vivosmart HR+ displays diverse fitness data on its screen) and smart things that rely on *intermediary* devices such as smartphones or tools (e.g., the smart lock Lockitron sends notifications via smartphone) [32]. The suitability of this distinction has been confirmed by the classification of the 200 smart things. In line with the definition of the interaction layer, a smart thing can also act via intermediaries, for example, by using Bluetooth, local Wi-Fi, or Internet. Since smart things can have own and intermediary acting capabilities, both characteristics are *non-exclusive*.

Autonomy: While smart things act autonomously in ever more scenarios, many neither learn nor act without external triggers [4]. We assign the autonomy level *none* to such smart things. For instance, the Situ food scale weighs food, displays the weight on a display, and sends information to the user's smartphone. At its local level, however, the scale needs to be operated conventionally. Other smart things operate in a *self-controlled* manner such as the smart vacuum cleaner Roomba. This robot is equipped with sensors and software to scan and clean floors, operating in an independent way without external interference to fulfil cleaning tasks unless exceptions occur [74]. More sophisticated smart things are even able to learn about their environment as well as adapt to their users' needs and preferences [4]. Such *self-learning* smart things can act and decide in line with goals, without external interference and in distinct cases even without external triggers. They continually refine internal models of themselves and their environment [74]. Self-learning smart things also take over decision-making from users [3, 19, 39]. As an example, the smart security camera Butterfleye learns the individual rhythm of home inhabitants and provides increasingly accurate alerts when something unexpected happens.

4.2 Interaction Layer

Also referred to as connectivity [41] or transmission [2], the interaction layer focuses on a physical thing's embedding into the digital world. For example, Internet connection enables remote access to a smart thing's sensing, acting, and computing capabilities [4, 41] as well as interactions among smart things [79]. Hence, the interaction layer covers the interaction *direction, multiplicity*, and *partners.*

Interaction Direction: Regarding the direction of interactions, a smart thing can participate in *unidirectional* and *bidirectional* interactions [3, 80]. Unidirectional interactions involve one-way flows of data. For instance, Babolat's smart tennis racket collects data during a game, which is forwarded to a user's smartphone. In bidirectional interactions, two or more partners are actively involved, and data flows in all directions. For example, the smart bracelet Olive, designed to reduce stress, uses haptic feedback to alert the user when it detects elevated stress levels. Users can also tap the bracelet to register that they are in a good mood.

Interaction Multiplicity: Smart things can also be classified in terms of the number of interactions in which they engage [4]. In *one-to-one* interactions, a smart thing connects to one interaction partner at a time [3]. For instance, the Lumo Run fitness tracker which attaches onto sports clothes and displays diverse fitness parameters on the user's smartphone, is designed for use by one person at a time. *One-to-many* interactions take place among multiple partners. For instance, the EverSense Location-Sensing Thermostat can track the location of all members of a family via their smartphones, and adjusts the temperature of their house after the last person leaves and before the first person returns.

Interaction Partner: Smart things can interact with partners. Bucherer and Uckelmann [79] define consumers, things, businesses, and service providers. We do not account for service providers but consider them as businesses. Further, Beverungen *et al.* [19] conceptualize smart things as boundary objects among businesses and consumers. Thus, we distinguish three types of interaction partners: *users, things,* and *businesses.* Conceptualizing users as interaction partners is straightforward: the use of any smart thing by an individual serves as example. Interactions among things are exemplified by the smart doorbell system Skybell: if the Nest smoke detector inside the house gives a smoke or carbon monoxide warning, the LED lights on the Skybell outside the house change to red, signaling that it is unsafe to enter. If detecting motion, Skybell triggers the Nest camera, which starts monitoring from inside the home. Finally, the smart bracelet QMedic is an example of a smart thing's interaction with a business: in case anomalies in mobility or sleep are detected, a call center is notified and in-home care provided. As a smart thing can interact with multiple partners, this dimension is non-exclusive [3].

4.3 Data Layer

Data is key in the digital economy [1]. In the IoT context, data may even constitute a smart thing's main value proposition [4, 19]. This is because smart things can locally process internal and external data and hence provide access to real-time data [40]. Accordingly, the data layer focuses on which data *sources* are used by a smart thing – be it collected through local sensors or exchanged with external sources – and on how smart things use data (*usage*).

Data Source: As for the data source, we distinguish between *thing state, thing context, thing usage,* and *cloud.* Thing state refers to the internal condition of a smart thing, covering data such as identity, charging, or operating status [2]. The thing context refers to a thing's physical environment (e.g., temperature or humidity), which is monitored via sensors [2]. Thing usage describes the data generated and processed during a smart thing's interactions with partners or users. Ultimately, smart things may have access to external data (e.g., weather forecast or energy prices) or additional enterprise data (e.g., warranty status) stored in the cloud. This also holds for other external sources, e.g., if a smart thing receives data directly from other smart things [40]. As a smart thing can process the input of different data sources, this dimension is non-exclusive [40]. The smart vacuum cleaner Roomba, for example, uses context data for coordination during the cleaning process. Furthermore, users can adjust its cleaning settings.

Data Usage: Data usage can be split into transactional and analytical categories [4, 40, 77]. *Transactional* usage refers to the processing of individual transactions or interactions. For instance, the smart shower Eva Drop collects data about the water temperature and the person's position in the shower and uses these data to adjust the water flow. In addition, data can be used for analytical purposes, which is commonly split into descriptive, diagnostic, predictive and prescriptive. We refer to descriptive data usage as *analytical basic*, while diagnostic, predictive, and prescriptive data usage is categorized as *analytical extended*. Smart things with basic analytical data usage enable descriptive analytics. The smart tracker Fitbit Charge, for instance, prepares the gathered data such as the distance run and the calories burned in order to provide them the user in an aggregated form. Analytical extended data usage provides more sophisticated analytics, as in the case of the smart camera Nest Cam IQ, which can identify via face recognition technology whether a person entering the house is a family member or a stranger.

4.4 Service Layer

With smart things driving the fusion of the physical and the digital world, the variety of enabled services is said to be "limited only by imagination" [40, p. 114]. Against this backdrop and in line with established IoT architectures, the top-most layer of the taxonomy relates to services associated with smart things [41]. It covers whether a smart thing provides offline functionality, a smart thing's value proposition, and its integration into ecosystems [4].

Offline Functionality: Connectivity is vital for smart things. In the IoT, the literature defines connectivity rather broadly, i.e., with a focus on a smart thing's general communication capabilities [32]. Rather than investigating specific communication technologies, we consider whether a smart thing's functionality depends on a working Internet connection, as this influences in which services a smart thing can be involved. If a smart thing cannot provide any functionality without a working connection, its offline functionality is classified as *none*. The WeMo insight switch requires a working connection to perform its functions: to remotely control home appliances and track their energy use. If a smart thing provides parts of its functionality without a working Internet connection, it is classified as *limited*. For example, the smart light bulb LIFX works like an ordinary light if it is turned on or off at the switch. To access colors and other features, it needs an active Bluetooth, local Wi-Fi, or Internet connection.

Value Proposition: In line with the bridging of the physical and the digital world, smart things consist of a physical underlying and a digital representation [81, 82]. That way, smart things serve as a distribution mechanism for digital services [76]. Against this background, smart things with a *thing-centric* and a *service-centric* value proposition can be distinguished. Smart things with a thing-centric value proposition primarily serve a thing-related purpose in the physical world extended by a digital representation and services [4]. An example is Babolat's tennis racket that helps players improve their game via an app, analyzing sensor data from the racket. Despite this valued-added service, the racket still retains its traditional functionality. Smart things with a service-centric value proposition also have a physical underlying, which primarily serves as a distribution mechanism. Related smart things cannot or hardly be used independently from digital services. For example, Amazon's Echo has no physical functionality but serves the provision of digital services (e.g., Alexa skills).

Ecosystem Integration: A priority in the development of smart things is to ensure that they not only collect and use data about themselves and their environment but also interact with other things [4]. This enables product systems, where smart things collaborate, and systems of systems that link product systems [4]. We refer to a smart thing's integration into such broader contexts as ecosystem integration and distinguish three characteristics: *none, proprietary,* and *open.* The June oven operates standalone and is not part of any broader IoT contexts. The characteristic *proprietary* refers to smart things that can be integrated into an ecosystem but which are only compatible with smart things from the same provider or manufacturer. For example, the smart camera Pivot is part of the Zmodo ecosystem. It can only be triggered by Zmodo sensors and controlled via the Zmodo app. Open ecosystem integration enables interoperability, covering smart things compatible with components across their own product family [40]. The Nest Thermostat, for instance, is equipped with an application programming interface (API) that allows information to be exchanged with products of other providers.

4.5 Classification Results and Examples

To evaluate the taxonomy and prepare the cluster analysis, two co-authors independently classified the 200 smart things. Specifically, 100% of the dimensions-specific hit rates exceeded 85% (Table 6) and 91% of the object-specific hit rates exceeded 75% (Appendix 2). These hit rates confirm that the taxonomy is clear in terms of dimensions and characteristics [48].

Table 6: Dimension-specific Hit Ratios

Dimension	Hit Ratio	Dimension	Hit Ratio
Sensing capabilities	96%	Data Source	93%
Acting capabilities	94%	Data Usage	89%
Autonomy	88%	Offline Functionality	95%
Direction	92%	Main Value Proposition	90%
Multiplicity	95%	Ecosystem Integration	86%
Partner	92%	Overall Hit Ratio	91%

Below, we exemplarily show the classification of two smart things from our sample to illustrate how the taxonomy can be applied to analyze existing smart things (Figure 3). These examples also illustrate the diversity of the smart things available on the market and covered by our taxonomy. As a first example, the Situ food scale has lean sensing capabilities for weighing food. Using own and intermediary acting capabilities, it shows the weight on its display and via an app. The scale is a non-autonomous device that needs a trigger for any action and interacts with one user at a time. It uses data for basic analytical purposes, e.g., the calculation of nutrients and calories. Without an Internet connection, the scale can be used as a conventional scale. Thus, it has limited offline functionality. This complies with the scale's thing-centric purpose. The scale is used independent from other smart things and not integrated in ecosystem.

Figure 3: Exemplary Classification of *Situ Food Scale* and *Nest Cam IQ*

	Dimension	Characteristics			
Service	Ecosystem Integration	None	Proprietary	Open	
	Value Proposition	Thing-centric		Service-centric	
	Offline Functionality	None		Limited	
Data	Data Usage	Transactional	Analytical (basic)	Analytical (extended)	
	Data Source	Thing State	Thing context	Thing Usage	Cloud
Interaction	Interaction Partner	User(s)	Business(es)	Thing(s)	
	Interaction Multiplicity	One-to-one		One-to-many	
	Interaction Direction	Unidirectional		Bi-directional	
Thing	Autonomy	None	Self-Controlled	Self-Learning	
	Acting Capabilities	Own		Intermediary	
	Sensing Capabilities	Lean		Rich	

	Dimension	Characteristics			
Service	Ecosystem Integration	None	Proprietary	Open	
	Value Proposition	Thing-centric		Service-centric	
	Offline Functionality	None		Limited	
Data	Data Usage	Transactional	Analytical (basic)	Analytical (extended)	
	Data Source	Thing State	Thing context	Thing Usage	Cloud
Interaction	Interaction Partner	User(s)	Business(es)	Thing(s)	
	Interaction Multiplicity	One-to-one		One-to-many	
	Interaction Direction	Unidirectional		Bi-directional	
Thing	Autonomy	None	Self-Controlled	Self-Learning	
	Acting Capabilities	Own		Intermediary	
	Sensing Capabilities	Lean		Rich	

As a second example, the indoor security camera Nest Cam IQ gathers vast amounts of data via rich sensing capabilities. It uses own acting capabilities (e.g., speaker) and intermediaries (e.g., smartphone or tablet), and is a self-learning smart thing learning how to differentiate between family members and strangers. The Nest Cam IQ interacts with users via microphone and has extensive capabilities to interact with other smart things. Apart from gathering data during usage and by monitoring its environment, it can access cloud data, including its video history. This enables extended analytical data usage, e.g., face recognition. Yet the Nest Cam IQ has no offline functionality and relies on its supervision service. It is compatible with smart things from the Nest ecosystem and third-party providers.

5 Smart Thing Clusters

Based on the classified sample, we indusctly inferred five clusters covering combinations of non-technical smart thing characteristics that typically occur together. Below, we introduce each cluster along with constitutive characteristics and real-world examples. The clusters are illustrated in Table 7 where we highlighted the most frequent characteristics per dimension. For non-exclusive dimensions, we included all characteristics covered by more than one third of the sample. Appendix 3 shows to which cluster the smart things from our sample were assigned.

To structure the clusters, we first split them according to the value proposition dimension, which was the first division performed by the cluster algorithm. We found that, in subsequent divisions of the cluster algorithm, the clusters remained either thing- or service-centric. Hence, we split them in a thing- and a service-centric group. In both groups, we also found sub-groups showing different but increasing levels of autonomy and ecosystem integration. In a nutshell, smart things can be grouped according to their value proposition and smartness, which in turn becomes manifest in autonomy and ecosystem integration. In line with these findings, we identified expressive names within the author team: *Standalone Thing-Centric Exectutants, Connected Thing-Centric Performers*, *Standalone Service-Centric Monitors*, *Connected Service-Centric Performers*, and *Self-Learning Service-Centric All-rounders*.

We evaluated the validity and reliability of both the clusters and the chosen names via the Q-sort. In a first scenario, two co-authors unfamiliar with the cluster results achieved a hit rate of 90% and a Kappa of 75%. In a second scenario, 15 researchers with an IoT background obtained a hit rate of 78% and a Kappa of 62%. These results reflect substantial agreement [83]. Detailed results are reported in Table 8.

Table 7: Smart Thing Clusters (most Frequent Characteristics)

		Cluster				
		Standalone Thing-Centric Executant	**Connected Thing-Centric Performer**	**Standalone Service-Centric Monitor**	**Connected Service-Centric Partner**	**Self-Learning Service-Centric All-rounder**
	Examples	*Oral-B smart toothbrush, smart fork Hapifork*	*Bosch's I-Dos smart washing machine, smart refrigerator Smart Instaview*	*RunScribe smart fitness tracker, Mon Baby sleep monitoring device*	*Wi-Fi connected garage control Garageio, Amazon Dash Wand*	*Nest smart thermostat, Cocoon smart camera*
Service	**Ecosystem Integration**	None	Open	None	Open	Open
	Value Proposition	Thing-centric	Thing-centric	Service-centric	Service-centric	Service-centric
	Offline Functionality	Limited	Limited	None	None	None
Data	**Data Usage**	Analytical (basic)	Transactional, Analytical (basic)	Analytical (basic)	Transactional, Analytical (basic)	Analytical (extended)
	Data Source	Thing context, Thing usage	Thing state, Thing context	Thing context, Thing usage	Thing context, Thing usage	Thing context, Thing usage, Cloud
Interaction	**Interaction Partner**	User(s)	User(s), Thing(s)	User(s)	User(s), Thing(s)	User(s), Thing(s)
	Interaction Multiplicity	One-to-one	One-to-many	One-to-one	One-to-many	One-to-many
	Interaction Direction	Unidirectional	Bi-directional	Unidirectional	Unidirectional	Bi-directional
Thing	**Autonomy**	None	Self-Controlled	None	Self-Controlled	Self-Learning
	Acting Capabilities	Own, Intermediary	Own, Intermediary	Intermediary	Own, Intermediary	Own, Intermediary
	Sensing Capabilities	Lean	Lean	Lean	Lean	Rich

[…]: total number of smart things (…): relative number of smart things

5.1 Cluster 1: Standalone Thing-Centric Executants

Standalone Thing-Centric Executants are everyday items with a thing-centric purpose enhanced by digital services. Most related smart things have lean sensing capabilities (87%), often provide own (68%) and always intermediary (100%) acting capabilities. Moreover, most related smart things are not autonomous (61%) and require external triggers for any action. Interactions occur with one partner (97%) who is the smart thing's user (100%). As for data usage, only basic data analytical purposes are supported (71%). In accordance with their thing-related purpose (92%), related smart things can perform at least some of their functionality without an Internet connection (95%). Finally, related things are not integrated into ecosystems (90%).

Two examples are the Oral-B smart toothbrush and the smart fork Hapifork, which observe brushing or eating habits and offer feedback via a smartphone. Independent from their digital services, they provide functionality as a toothbrush or fork. Furthermore, the analytical capabilities of both smart things are restricted to analytical basic. Finally, both smart things only interact with their users and are not integrated into any ecosystems.

Table 8: Cluster-specific Hit Ratios

		Classification according to cluster analysis				
	Cluster	Standalone Thing-Centric Executant	Connected Thing-Centric Performer	Standalone Service-Centric Monitor	Connected Service-Centric Partner	Self-Learning Service-Centric All-rounder
Classification by participants	Standalone Thing-Centric Executant	**91%**	0%	11%	0%	0%
	Connected Thing-Centric Performer	0%	**71%**	1%	18%	8%
	Standalone Service-Centric Monitor	9%	2%	**76%**	13%	2%
	Connected Service-Centric Partner	0%	27%	11%	**69%**	5%
	Self-Learning Service-Centric All-rounder	0%	0%	1%	0%	**85%**

5.2 Cluster 2: Connected Thing-Centric Performers

Connected Thing-Centric Performers are everyday items integrated in broader IoT contexts. Most have lean sensing capabilities (83%) as well as own (93%) and intermediary (93%) acting capabilities. They also have a thing-centric purpose (98%). After an initial trigger, a small majority of related smart things can act in a self-controlled way without user interference (53%). Interactions typically occur with more than one partner (95%), mostly with users (98%) and other things (43%). Connected Thing-Centric Performers implement transactional (45%) or basic analytical (45%) data usage capabilities. Most related smart things can perform parts of their functionality without Internet (95%). Thing-Centric Performers are typically integrated into ecosystems (68%). While some are only compatible with products from the same provider (18%), half (50%) of them can interact with other providers' products.

Examples are Bosch's I-Dos smart washing machine, with its automatic dosing system, and the smart refrigerator Smart Instaview, which includes features such as voice control. The functionality of both smart things is bound to the physical product and they can exist independently from additional services. Both I-Dos and Smart Instaview can be controlled via an app, and may be integrated into ecosystems established by multiple associated partners such as Bosch Home Connect or Google Home.

5.3 Cluster 3: Standalone Service-Centric Monitors

Standalone Service-Centric Monitors are smart things that monitor their environment or users without being integrated into ecosystems. Most related smart things possess lean sensing capabilities (71%) and intermediary acting capabilities (100%, only 22% also have own acting capabilities). This implies that the thing itself primarily serves as distribution mechanism of digital services. Most Standalone Service-Centric monitors are not autonomous (55%), while others function without user intervention (43%). Furthermore, most Standalone Service Centric Monitors interact with only one partner (59%), who is nearly always their user (98%). Data is collected while the thing is in use (77%) or gathered through monitoring the physical environment (47%). Data is mostly used for basic analytical purposes (69%). Without an Internet connection, almost no functionality is available (92%). Finally, most Standalone Service-Centric monitors are not integrated into ecosystems (92%).

Examples include the RunScribe smart fitness tracker and the Mon Baby device which monitors a baby's sleep. Both devices consist of a clip attached to a running shoe or baby's shirt without own acting capabilities. The clip monitors running performance or sleep and enables analyses through an app. Hence, the smart thing itself primarily serves as a distribution mechanism for digital services and is unusable without the app, which is provided on an intermediary device.

5.4 Cluster 4: Connected Service-Centric Partners

Connected Service-Centric Partners are smart things with well-developed connectivity and compatibility. Almost all related smart things have lean sensing capabilities (97%). More than half have own acting capabilities (53%) and the clear majority has intermediary (94%) acting capabilities. Related smart things are either self-controlled (53%) or not autonomous (44%). Most can interact with more than one partner (88%), and Connected Service-Centric Partners do not only interact with users (97%) but also with other things (72%). Data is usually drawn from the thing's context (69%) or is collected while the thing is in use (53%). More than half of the Connected Service-Centric Partners use data transactionally (53%), whereas basic analytical data usage only occurs in just over one-third (34%). Without an Internet connection, no functionality is available (100%). Another feature is that most related smart things support open ecosystem integration (72%).

Examples include the Wi-Fi connected garage control Garageio, which consists of a black box installed in a garage, and the Amazon Dash Wand, a connected Alexa-enabled home barcode scanner. Both smart things primarily serve as distribution mechanisms for services and are integrated into ecosystems, working with other smart things and services such as Amazon Echo.

5.5 Cluster 5: Self-Learning Service-Centric All-rounders

Self-Learning Service-Centric All-rounders are sophisticated smart things that have high autonomy and are integrated into IoT ecosystems. They have rich sensing capabilities (90%), and usually have own (92%) and intermediary (97%) acting capabilities. Many Self-Learning Service-Centric All-rounders can take over decision-making tasks from users at which they improve over time (41%). Despite the share of only 41% self-learning devices, this cluster includes 89% of all self-learning devices from our sample. Self-Learning Service-Centric All-rounders interact with users (100%) and other things (49%), and the majority can interact with more than one partner (85%). Data is collected from the thing's environment (54%) or usage and, in some cases, from the cloud (39%). Most related smart things use data for extended analytical purposes (56%). Finally, most related smart things can be integrated into different ecosystems (69%) and many are compatible with products from other providers (54%).

One example is the Nest smart thermostat, which learns and automatically adapts to its users' behavior by re-configuring itself. It also works with lights, locks, and other products, and is compatible with different providers. A second example is the smart camera, Cocoon, which learns the unique patterns of a home and improves over time to avoid false alarms.

6 Conclusion and Outlook

6.1 Contribution and Implications

In recent years, the IoT has attracted considerable attention, as it affects our private and business lives in diverse domains. Although huge potential is attributed to the IoT, most works either treat smart things as black box or focus on technical characteristics. From an engineering management perspective, however, also an understanding of non-technical smart thing characteristics is key to tap the full potential of the IoT. Hence, we set out to investigate such non-technical characteristics. Below, we discuss the implications of our research as well as limitations and an outlook on future research. Table 9 provides a management summary.

Table 9: Overview of Contributions, Implications, Limitations, and Outlook

Contribution	
1.	Taxonomy of non-technical smart thing characteristics structured according to established IoT architectures
2.	Clusters of smart things representing typical combinations of characteristics occurring in practice
Theoretical implications	
1.	Classification of smart things on two granularity levels
2.	Operationalization of existing IoT architectures through dimensions and characteristics of the taxonomy
3.	Complementation of existing works with a focus on technical smart thing characteristics through non-technical characteristics
4.	Update of existing works with a focus on non-technical smart thing characteristics through a broader sample and latest literature
Managerial implications	
1.	Smart things should not be treated as black box
2.	Smart things can be clustered on a high level according to their value proposition, autonomy, and ecosystem integration
3.	The design space of smart things has not yet been fully explored
4.	The clusters assist in strategic product portfolio decisions, while the taxonomy assists in early phases of product development
Limitations	
1.	Sample is limited to 200 smart things and the B2C context
2.	Clusters are not perfectly disjoint owing to inductive clustering
Outlook	
1.	The taxonomy should be updated from time to time and challenged through an extended sample
2.	Setting the focus of the role of the individual smart thing in broader contexts such as IoT ecosystems
3.	Research on adoption and affordances of smart things should be conducted
4.	Research on methods for the analysis and design of smart things should be conducted

Our theoretical contribution is twofold: First, we proposed a literature-backed and broadly validated taxonomy of non-technical smart thing characteristics, which enables the in-depth classification of individual smart things, based on the latest IoT literature and the latest generation of 200 smart things deliberately chosen from diverse IoT application domains. The dimensions included in the taxonomy are grouped according to the layers of established IoT architectures to foster the taxonomy's understandability and to cover relevant perspectives on smart things ranging from physical product to digital service. Including multiple dimensions per layer, the taxonomy not only draws from but also operationalizes existing IoT architectures. By covering all layers of IoT architectures, the taxonomy complements the focus on technical characteristics of existing works such as Barker *et al.* [22], Dorsemaine *et al.* [23], López *et al.* [24], and Mountrouidou *et al.* [25]. Moreover, the taxonomy updates and extends Püschel *et al.*'s [26] work, as we confirmed dimensions (e.g., sensing capabilities and data usage), dropped dimensions (e.g., main purpose and thing compatibility), and found new ones (e.g., ecosystem integration and autonomy). Most specifically, the taxonomy supports the effective discussion of commonalities and differences of smart things, an important foundation for scientific progress and the capitalization of the IoT in industry [45, 46].

As our second theoretical contribution, we inductively inferred and validated five smart thing clusters based on the classified sample. Each cluster represents a typical combination of non-technical smart thing characteristics. The clusters abstract from the combinatorial diversity of smart things and provide high-level insights into the smart things on the market. We specifically found that value proposition, ecosystem integration, and autonomy are key for discussing smart things on a coarse-grained level. Overall, our results demonstrate that the diverse set of smart things on the market can be abstracted into specific artefacts, i.e., a taxonomy with a manageable number of dimensions and a manageable number of smart thing clusters.

Our results have the following implications for engineering managers:

- First, smart things should not be treated as black box but should be classified according to defined characteristics, which determine how they can be used by individuals and be integrated in organizations' value propositions.
- Second, the clusters revealed similarities among smart things on a coarse-grained level. This implies that engineering managers need not cope with the full combinatorial diversity set up by the taxonomy when analyzing smart things and that the design space of smart things has not yet been exhausted. Hence, there is a huge potential for new product offerings.
- Third, our results support various decisions of engineering managers. A cluster-based high-level analysis is reasonable in use cases such as strategic product portfolio decisions, before engaging in detailed discussions related to specific product design ideas in early phases of

product design using the taxonomy for structuring the design space of smart things. Moreover, knowledge about technical smart thing characteristics from existing works is relevant in later phases of product development, when smart products are implemented. In our own industry projects, the taxonomy and the clusters helped to analyze the smart things of competitors as well as enhance existing and creating new products. Moreover, they helped to match the characteristics of smart things and customer needs, derive design recommendations, and create rough cost estimates as foundation of early go/no go decisions.

- Fourth, engineering managers can use our findings beyond product development to account for the action possibilities of smart things in process reengineering projects and to assess respective performance effects (e.g., time, cost, quality, and flexibility). This includes not only own processes but, in line with our focus on the B2C context, also the processes of consumers who use one's smart product offerings.

Apart from these implications, we successfully applied the taxonomy and the clusters in research (e.g., related to the design of smart things and the business value of IoT-based offerings) and industry projects (e.g., related to design of IoT-based solutions and business models). Hence, our findings already shaped up useful for diverse stakeholders.

6.2 Limitations and Outlook

As any research, our work is beset with limitations. First, despite carefully selected 200 smart things, our sample is restricted to a certain period and focuses on the B2C context. Given the fast-moving nature of the IoT, it is likely that so far under-represented characteristics will become common and that new characteristics will emerge in the future. Moreover, as the clusters were inferred inductively from the sample, some blurring was unavoidable. Hence, the taxonomy and the clusters should be reassessed from time to time to account for new developments. We also restricted the sample to smart things from B2C contexts as much more information is publicly available. Nevertheless, research should challenge how the taxonomy needs to be extended to fit other contexts. A corresponding sample should include smart things from the B2B context, e.g., smart factories. Finally, we admit that, despite its focus on the B2C context, the sample is broad in terms of the included smart things' diversity. In our opinion, this is a feature not a bug, as the development of a broadly applicable taxonomy and clusters, which cover the full range of smart things available on the market, requires such a sample.

Second, in line with our research question, the taxonomy and the clusters take the perspective of individual smart things. However, the IoT will not unfold its potential if smart things remain the center of interest in research and industry. Hence, research should also focus on the role of smart things in IoT ecosystems. Our findings can serve as foundation for such research.

Finally, our findings stimulate future research on the IoT. From a descriptive view, the identified non-technical characteristics and the clusters may serve as input for exploring drivers related to the adoption and use of smart things. They can also serve as foundation for further investigating affordances of smart things. From a prescriptive view, our results inspire research on developing methods for the analysis and design of smart things as well as on extending existing product design and process reengineering methods with respect to smart things.

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