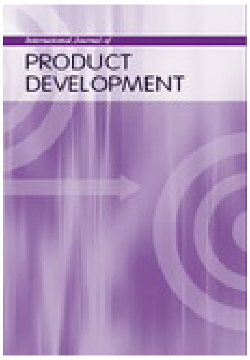

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Data-intensive IoT new product development: a review and future directions

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Data-intensive IoT new product development: a review and future directions

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Abstract: Commonly referred to as data-driven product development, incorporating data science into product development to create value out of sensor data is a key challenge and involves unpredictability and invention risk. However, different studies in the current literature rely on different conceptualisations in this interdisciplinary research field, and the literature is scattered. To address this issue, this paper provides a review of recent academic literature on New Product Development (NPD) for the Internet of Things (IoT). The work reveals that distributed literature lacks a standardised process for guiding managers to handle the data product development process of smart products.

Keywords: internet of things; new product development; smart product; data science; sensors; data-intensive; data-based value creation.

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1 Introduction

More and more physical products feature IoT components (Sheen, 2019). Such products are capable of sensing and acting upon their environment using digital sensors and actuators. They can exchange data over home, industry or wide area networks. Furthermore, these 'smart products' (Raff et al., 2020) feature more or less sophisticated algorithms that enable the product to learn from and adapt to its environment. Consequently, they gain some degree of intelligence that makes them more useful to the end user. The process of developing and integrating this intelligence, i.e., data science, comes with its own set of challenges. Companies that have developed only physical goods in the past may lack, or may not even be aware of, the necessary data analytics capabilities (Mikalef et al. 2018) to drive their own digitalisation effort. Consequently, they join up with interdisciplinary data science projects (Crisan et al., 2021) that complement their own capabilities. Crisan et al. (2021) call this 'multi-disciplinary product design'.

They suggest that each discipline can work concurrently. However, any sufficiently innovative IoT NPD project faces a dilemma when developing both the 'cyber' and the 'physical' parts of the new product at low Technological Readiness Levels (TRL) (Mankins, 2009). On the one hand, data science requires reliable data sources that generate consistent data. But the data source, i.e., the physical product and its sensors, is itself still in development and a prototype at best. On the other hand, advancing the physical product requires further insights from data science. This includes answers to critical questions like: Are we measuring the right type of data? Are the sensors correctly sufficiently sensitive, correctly configured and placed? Is the network connectivity reliable enough? Hypotheses on the realisability of the new product or its components may be proven false late in development, which can have significant impacts on the product's value proposition.

We argue that this type of data-intensive IoT NPD, which requires multi-disciplinary effort to advance and combine low TRL data science and physical components, is insufficiently discussed in current NPD literature. In contrast to typical NPD, it differs in terms of risk, uncertainty, unpredictability, scope and costs (Aristodemou et al., 2020; Gassmann and Schweitzer, 2014). More specifically, knowledge discovery from sensor data (Wirth and Wirth, 2017) and the corresponding fitness-for-use analyses of sensor technology are complex and heterogeneous problems. Product life cycles and data life cycles are becoming more similar, and the associated challenges include different innovation cycles, development times and volatile interdisciplinary requirements.

The factors characterising the early stages of data-intensive IoT product development are not well known; in fact, little research has been conducted on how to handle the new complexity arising from the IoT sensor data used in smart product development compared to that in many other activities in NPD (Marzi et al., 2021). Moreover, it is essential to reach a consensus on the critical factors that influence this process in its early stages. The challenges of managing analytical methods within IoT NPD to ultimately add value should be considered (Kayser et al., 2018).

This article aims to establish a starting point towards a comprehensive process model that can incorporate the aforementioned complexities of data-intensive IoT NPD by systematically reviewing current IoT NPD literature. Its research questions are as follows:

- *RQ1*: What are the characteristics of existing data-intensive IoT NPD process models?
- *RQ2*: How does recent scientific literature consider specific steps in developing data-intensive IoT NPD?

The rest of this paper is structured as follows. First, the review approach followed in this study is described in Section 2. Section 3 summarises the literature findings on the opportunities and challenges of incorporating data science into the FEI of IoT NPD. Section 4 discusses the results and presents requirements for a normative process model. Section 5 gives the conclusion of the work and provides recommendations for future research.

1.1 Background

The proliferation of the Internet of Things (IoT) including connectivity and Artificial Intelligence (AI) has enabled the addition of new hardware and software to previously analog products, e.g., integrating sensors into ski boots for instant on-slope feedback, referred to as 'smart products' (Raff et al., 2020). Recently, products have been designed to include smart and physical components (Porter and Heppelmann, 2014). This has increased interest in digital–physical product development by using IoT over the past decade (Hendler and Boer, 2019). A recent paper highlighted the 'major transformation' and 'significant impact' of IoT on the development of new products. Further, another article has highlighted the growing digital transformation of previously physical manufacturing industries, creating new revenue streams through IoT (Euchner, 2019). Managing the development of smart products is still a topic of concern (Huikkola et al., 2021).

The 'data-driven innovation' paradigm of New Product Development (NPD) has emerged for handling the development of smart products (Bstieler et al., 2018). According to the Organisation for Economic Co-operation and Development (OECD), the term 'data-driven innovation' refers to innovative applications derived from data analytics. Different technologies and techniques define and capture, process, and analyse relevant data (OECD, 2015). Data for innovation can be extracted from people (human data, such as captured biomechanical or vital parameter data) and specific objects (such as Industry 4.0 or Google NEST devices) (Lim et al., 2018). Different sensor setups for these data sources can collect and digitise data depending on the activity of interest (Farias da Costa et al., 2021). However, particularly for technology projects in early-stage, sensor data pose several challenges, including the need to clean data, high-resource consumption, complex built-in algorithms, descriptive and predictive models and hardware and software artefacts (Krishnamurthi et al., 2020; Porter and Heppelmann, 2015). Despite the popularity of IoT and NPD as research areas, little research has been conducted on how to deal with the technical and physical limitations of IoT sensor data in front End of Innovation (FEI) (Lee et al., 2022; Gassmann and Schweitzer, 2014). Compared to traditional NPD, the combination of IoT with NPD is a relatively new phenomenon in fuzzy front-end theory. Consequently, the importance and impact of data-driven design in new product development require significant attention (Briard et al., 2021). The ability to turn data into knowledge (Portela, 2021) has become a critical component, complementing the product development process (Li et al., 2019). However, publications in this field have mainly focused on approaches linking data-rich business environments and their implications for NPD and innovation (Bharadwaj and Noble, 2015). Other recent research on innovation and NPD focuses on the impact of big data analytics, IoT and innovation (Bstieler et al., 2018; Fu and Asorey, 2015).

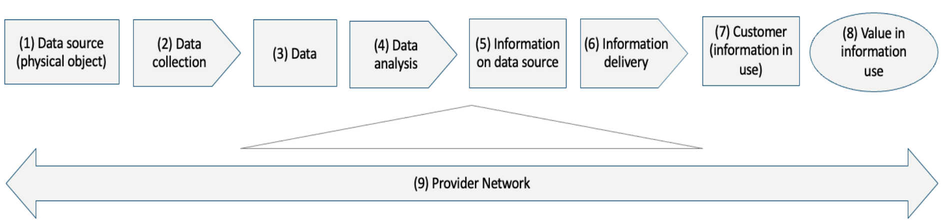
Furthermore, data-driven IoT products have not been rigorously defined, and the researchers have proposed several definitions. Davenport and Kudyba (2016) described a 'data product' as one that 'combines data with analytical capabilities,' focussing on how data are offered as an asset. Chen et al. (2011) distinguished two types: data as a service and analytics as a service focusing on the contributions that enable customers to analyse large data sets. Hunke et al. (2020a) describe it as 'a new type of service that builds upon data and applies analytical methods ('analytics') assisting customers in making better decisions and solving more complex problems.' Furthermore, Patil et al. (2019) defined a data product as '… a product that facilitates an end goal through the use of data'. Finally, Li et al. (2019) and Lim et al. (2018) referred to a data product as one where 'data is used to create data-driven machine-learning features within a smart product.' Thus, as with the term 'smart product' (Raff et al., 2020), there is no consensus about 'data products,' and literature lacks a standard definition. In this research work, a data product is associated with the attributes of an AI innovation outcome in smart product development, i.e., using sensor-based data from an IoT device. Although narrowing the definition as a 'data-intensive IoT product' is the most appropriate, there is a need to understand the conceptualisation further.

2 Methods

We investigated the concepts presented in recent papers on NPD to describe the tasks and strategic decisions needed to develop data-intensive IoT products creating business value from data for answering RQ1. An extensive review was conducted to explore the interdisciplinary and complex nature of IoT NPD (Von Elm et al., 2019; Peters et al., 2020). It allows us to explore relevant concepts and types of evidence to identify research gaps (Colquhoun et al., 2014). Furthermore, to answer RQ2, we have analysed the visible steps involved in developing data-intensive IoT products in IoT NPD from the existing literature. In particular, it critically examines methodological approaches and explores the steps considered in the current IoT NPD literature for the development of data-intensive IoT products.

The data value chain (Lim et al., 2018) in Figure 1 was adopted as the theoretical framework for classifying the relevant studies as it includes both the physical IoT product (i.e. (1) Data source) and the data science perspectives. This process consists of nine steps that are applied to develop and manage data-intensive IoT products: 1) definition of a data source, 2) data collection, 3) data, 4) data analysis, 5) information on the data source, 6) information delivery, 7) customer, 8) value in information use and 9) provider network. Unlike other reference process models used in data science, such as the Cross Industry Standard for Process Mining (CRISP-DM) (Chapman et al., 2000), the data value chain considers the physical perspective (i.e., the data source) and its complexity. Furthermore, while the model includes the data collection phase with data sources in the early stages of development, traditional data science process models assume that data sets already exist, which is not valid for most smart product development processes.

Figure 1 Data value chain (Lim et al., 2018)



2.1 Search query and databases

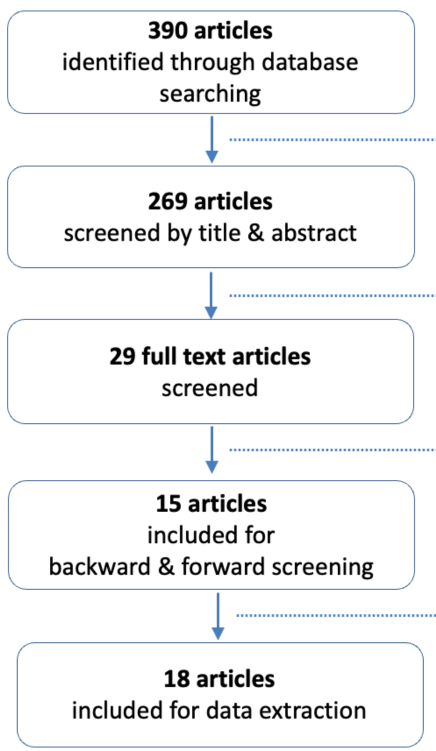
First, a literature search was conducted in the areas of NPD, IoT and Data Science to determine an appropriate period for the search. A study was undertaken to find research literature relevant to knowledge discovery and data mining in the field of smart product development and services based on IoT sensor networks. This included both descriptive and prescriptive work and treatments of data product development about design and development process models. From the reviews recently published by Götz et al. (2018); Wynn et al. (2019) and Hendler and Boer (2019), the bibliographies of these articles were studied. Then, we identified relevant sources and studied their bibliographies.

Consequently, the period from 2015 to 2021 appeared to be realistic. The databases Scopus, Web of Science and EBSCO were considered to have an adequate and comprehensive collection of literature. Because IoT NPD is an inherently interdisciplinary field, the final search string for identifying the current body of literature was developed iteratively with experts from innovation management, technology development, and data science. The first search query spanned all the related domains. It included design and process models for NPD and technology development: *('NPD' OR 'product development' OR 'technology development' OR 'process model' OR 'digital innovation').* We defined the second query as *('smart product' OR 'IoT' OR 'Internet of Things') AND ('data-driven OR 'analytics' OR 'AI' OR 'data science' OR 'knowledge')* to include smart product development and data science.

2.2 Literature search process and inclusion criteria

Figure 2 illustrates the process followed for the literature search using a PRISMA chart.

Figure 2 Flow chart showing the literature search process



We limited the results to peer-reviewed publications in English. Conference proceedings from peer-reviewed conferences were also included, as technological developments are often presented at conferences. The search yielded 390 articles (EBSCO: 50, Scopus: 232, Web of Science: 108). After duplicate removal, 269 articles remained for further screening. In the first step, articles were screened based on their title, keywords and abstract, using a process followed in recent reviews (Hendler and Boer, 2019). Consequently, 29 articles were selected and evaluated based on full text. The screening process involved two stages with the following inclusion criteria: (a) publications that focused on IoT NPD or one of its process steps and (b) publications that partially focused on integrating data or analytics. Exclusion criteria included publications not in the period January 2015 until March 2021, text not in English, not related to product development and NPD papers with no IoT focus. Furthermore, forward and backward searches (Webster and Watson, 2002) through Google Scholar and the previously mentioned databases yielded three more articles, for a total of 19 reviews to be analysed.

2.3 Sample description

The final set of articles is summarised in Table 1 in chronological order, and a descriptive summary of the process models followed. The chronological distribution of the articles (see Figure 3) shows that interest in the field of IoT NPD increased after 2017, reflecting the novelty and growing importance of this research area. Of the articles in our sample, 84% (16 out of 19) were published between 2018 and 2021. Additionally, we added as a high relevant publication recent work of Lee et al. (2022) which evolved within the last year during the journal review process of this work. 12 of the 19 articles were published in peer-reviewed journals, 2 in high-quality magazines (MIT Sloan Management and Harvard Business Review) and 4 in conference proceedings.

Figure 3 Chronological distribution of the final set of articles

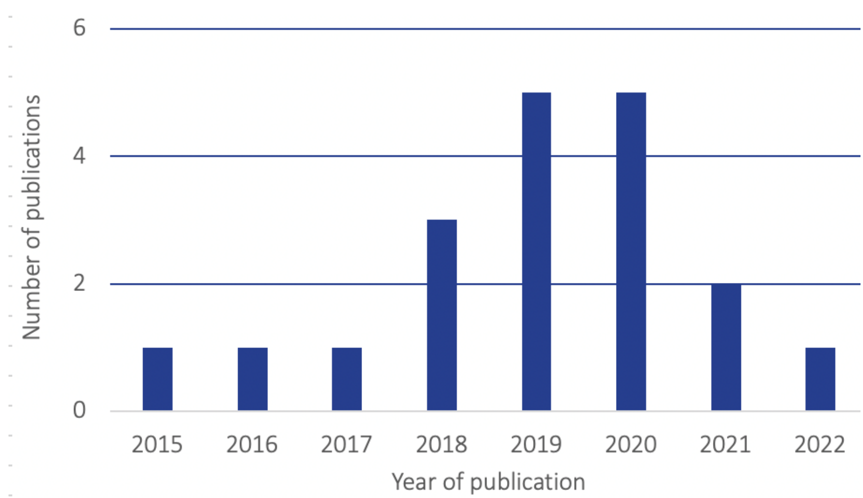


Table 1 gives a descriptive summary of the process models in our final sample of papers.

Table 1 Summary of the selected articles

Authors, year	*Short description of the process model*
Porter and Heppelmann (2015)	The authors propose a process model consisting of four steps. The iterative process begins with identifying the data sources (external, smart connected products, enterprise). The next step involves transferring to the data lake, followed by analytics. The last step is to create deeper insights for the business, customers and partners.
Davenport and Kudyba (2016)	Based on Meyer and Zack's (1996) work, this is one of the few process models in data product development. Two additional steps are included in the process model: conceptualising the product at the front end and establishing a market feedback mechanism at the back end.
Lewandowski and Thoben (2017)	Similar to Wilberg et al. (2018) developed a process model for applying different sensor systems and condition monitoring systems in the context of maintenance. Their procedure consists of five steps: drafting (functional, hierarchical analysis), development of, e.g., sensors, integration of field data and algorithm development, commissioning including, e.g., trials and operation.
Holler et al. (2018)	The authors propose a set of methods for creating digitised products. Specifically, they refer to system and architecture modelling for a multidisciplinary engineering process.
Sjöman et al. (2018)	This process model is based on a retrospective view of developing a medical device measuring human balance. It contains six steps; the starting point involves validating the iterative principle, followed by iterative hardware and data validation processes. The fourth step involves iterative validation with end-users, and the final step is integrating the system with user feedback. The results of this process form the basis for pilot studies. The authors also emphasise the consequent external (i.e., prototype data) abstraction and internal (i.e., final device) iteration loops.
Wilberg et al. (2018)	The process model is divided into six steps and focuses on the creation of a data strategy for the use phase. The objectives and use cases are determined in the first steps. The next step is to determine the data requirements. Following that, the use cases are evaluated, and finally, a roadmap for implementation is derived.
Blagoeva and Belsoska (2019)	The author uses work by Davenport and Kudyba (2016) as a foundation for introducing three dimensions for an effective innovation process when developing data products: (1) R&D capability, market opportunity and executive champions (enablers of emerging market innovation); (2) market need, portfolio fit and product-capability fit (strategic) and (3) product development (decision matrix, bootstrapping).
Li et al. (2019)	This NPD model is based on the CRISP-DM model (Chapman et al., 2000), the Stage-Gate (Cooper, 2010) and the NPD model of Ulrich et al. (2020). The authors align the 'business understanding' stage of CRISP-DM with the planning stage of NPD. The model is divided into three perspectives: (1) data product development, (2) project management and (3) physical product development. In the concept development phase, the paper investigates the interactions between engineering and data science tasks.

Table 1 Summary of the selected articles (continued)

Authors, year	*Short description of the process model*
Schuh et al. (2019)	Although the authors do not describe the process itself, they propose a morphology describing important digital features and functions to be considered when developing smart products. Examples include the type of data collection, degree of intelligence and the type of interaction.
Tomiyama et al. (2019)	The authors create a feasible multidisciplinary product development process divided into three domain-wide steps. Starting with requirements as step 1, the second is concerned with (mechanical and electronic) behaviour. Hardware and integration are included in the third step.
Zhang et al. (2019)	This design model for complex product development consists of four steps. The first involves the development and design data, and the output forms the input to the other three development and design steps, which are carried out using a closed feedback process based on (1) resources, (2) tasks and (3) applications.
Al-Fedhly and ElMaraghy (2020)	This work uses a V-shaped model as its foundation and proposes a concurrent multidiscipline product cyber-physical product design and evolution methodology. The design development, component development and product integration are conceptualised separately.
Cantamessa et al. (2020)	The purpose of this paper is to present a conceptual framework for the design of data-driven NPD processes. In a continuous development process, the authors refer to a 'seed design', which is iteratively improved and extended.
Dremel et al. (2020)	To specify the implementation stage, the authors employ an archetypical process for developing analytics as a service. The process begins with an exploration phase that includes an evaluation of ideas and internal feasibility, as well as an initial evaluation of technological readiness and analytical expertise/capabilities. The authors emphasise the importance of determining the organisation's development readiness and propose three paths based on the level of readiness.
Edu et al. (2020)	From a capability theory and a resource-based view of information systems, the authors create a conceptual model for digital innovation deployment and creation. Consisting of four pillars the process model support companies in the process of data sourcing, processing, and storage: (1) a resource-based view, (2) an IT capability view, (3) digital innovation benefits and (4) firm benefits/value creation.
Lee et al. (2020)	The process model is conceptualised in an iterative cycle that starts with the discovery phase, allowing customers to understand how they would benefit from the IoT system. The next step is the 'define' phase, in which the level of smartness of the system is evaluated to find the right solution. The 'development' phase is then applied. Emphasis is placed on access to numerous users to test and refine algorithms. Finally, the 'delivery' phase involves curating data and adding meaningful value by speaking to stakeholders.
Lee et al. (2022)	The authors propose a conceptual model named 'Mobius strip model' by integrating development strategies from three perspectives: i) physical product development and 2) software development and 3) data-science. Through layers and loops activities are merged towards a holistic approach for IoT NPD.

Table 1 Summary of the selected articles (continued)

Authors, year	*Short description of the process model*
Briard et al. (2021)	The paper presents results from a review and workshop regarding data-driven design challenges. As a result, the authors propose a future research agenda for a shift in the data-driven design paradigm including (i) methods and frameworks development, (ii) guideline & tools development, (iii) organisation of product design, (iv) establishment of ethical rules and (v) exploring limits of data-driven design.
Thongprasert and Jiamsanguanwong (2021)	The systematic review focuses on IoT NPD in medical device development. As a result of the study, the authors describe a design process for IoT home-medical devices. Emphasis is mainly placed on user acceptance arising from new functions and attributes from IoT devices.

2.4 Analysis and synthesis process

The analysis and synthesis process aimed to summarise and analyse existing research on design and development approaches that support the operation of IoT NPD. The gaps in the literature were identified based on the summary. The final set of 19 articles was analysed using a concept matrix (Webster and Watson, 2002). It has one dimension with the selected publications and another with the concepts and characteristics. Each article was classified on the following concepts: the type of contribution, the research perspective and the identification of the process steps of the data value chain element(s). The research perspective reflects the various strands of research in the interdisciplinary field of IoT NPD. It is well-known that the range of terminology used to describe the NPD is comprehensive (Marxt and Hacklin, 2005). The type of contribution represented the approach used to formalise the activities in IoT NPD and was derived from each article using a deductive approach. Finally, the data value chain indicated the steps of the data-intensive IoT NPD from the reports. The categories were defined according to the nine steps proposed by Lim et al. (2018).

3 Results

Table 4 gives an overview of the 19 articles analysed in our review and shows how the examined articles differ in three concepts mentioned in Sub-section 2.4. If authors do not explicitly address one element of the data value chain, but the development was described within bigger categories (e.g., Lee et al., 2020 summarise several steps into ‘Technical discussion’), the appropriate cells of the data value chain were merged.

Table 2 Concept matrix for the analysed literature

	Design	*Product development*	*Product innovation*	*Process*	*Framework*	*Method*	*Architecture*	*(1) Data source*	*(2) Data collection*	*(3) Data*	*(4) Data analysis*	*(5) Information*	*(6) Information delivery*	*(7) Customer (information use)*	*(8) Value in information use*	*(9) Provider network*
Porter and Heppelmann, 2015			x		x			x		x	x	x	x	x	x	x
Davenport and Kudyba, 2016			x	x				x		x		x	x	x	x	
Lewandowski and Thoben, 2017	x			x				x	x	x	x	x		–	x	
Holler et al., 2018			x			x		x		x	x	–	x	x	x	
Sjöman et al., 2018	x			x				x			x		x		x	x
Wilberg et al., 2018	x			x				x		x	x	x		x	x	
Blagoeva and Belsoska, 2019			x	x				x		x		x	x	x	x	
Li et al., 2019		x		x				x	x	x	x	x		x	x	
Schuh et al., 2019		x				x		x	x		x	x	x		x	
Tomiyama et al., 2019	x			x				x	x					x	x	
Zhang, et al., 2019	x						x		x			x	x		x	x
Al-Fedhly and ElMaraghy, 2020	x					x		x		x	x	x	x	x		
Cantamessa et al., 2020	x				x			x	x	x	x	x	–	x	x	x
Dremel et al., 2020	x						x		x				x		x	
Edu et al., 2020			x		x			x			x	x			x	x
Lee et al., 2020	x			x				x			x			x	x	x
Lee et al., 2022	x			x					x	x	x		x	x	x	
Briard et al., 2021	x			x				x			x			x	x	x
Thongprasert and Jiamsanguanwong, 2021	x			x				x			x			x	x	x

3.1 Research perspectives

Examining the literature shows that different perspectives have been applied to explore the design and development process in IoT NPD. Owing the nature of NPD, contributions can be located within procedural models that convey recommendations for best practices (Wynn et al., 2019). However, our review reveals that knowledge in IoT NPD is dispersed and contains various contributions from different research communities. The terms 'design', 'product development' and 'innovation' have emerged and can be distinguished based on the process steps (Marxt and Hacklin, 2005). Therefore, the articles in the literature were divided into these three categories, following the definitions given in Table 3. The most frequent perspective was 'Design' (9 articles), followed by 'product innovation' (5 articles) and 'product development' (2 articles).

Table 3 Terminology according to Marxt and Hacklin (2005)

Terminology	*Process steps included*	*Focus*	*Characteristic*
Design	Focus on development and validation	Functions or concepts	Very detailed, with a great deal of specific knowledge
Product development	Focus on development and validation, but also market introduction and product review activities	Product, process, service	Aggregated view
Product innovation	Focus on the overall process, including strategic considerations for product development and market introduction	Business model	focuses on the business aspects of bringing a product to market.

Design process models describe further development and validation steps, thus providing detailed and specific knowledge (Marxt and Hacklin, 2005). They can be further divided into an engineering and technology view (Lewandowski and Thoben, 2017; Sjöman et al., 2018; Tomiyama et al., 2019; Dremel et al., 2020; Al-Fedhly and ElMaraghy, 2020), a data-driven design view (Wilberg et al., 2018; Cantamessa et al., 2020; Briard et al., 2021) and a more general design process view (Lee et al., 2020, 2022).

Two publications addressed the *product development processes* through which data product development was incorporated into the IoT NPD processes. The paper by Li et al. (2019) was the only one to focus on a product development process that included data-intensive IoT development in the concept phase of NPD. Nevertheless, we identified product development process descriptions that supported the generalised representation of a development process by focusing on key elements such as data collection, analytics activities or value creation. The studies in the sample used a range of research approaches and mainly included projects in an industrial (Holler et al., 2018; Wilberg et al., 2018; Schuh et al., 2019; Dremel et al., 2020) or university context (Li et al., 2019).

Fewer publications focused on product *innovation* processes, including strategic considerations for product development, market introduction and effects on business models. These activities included a review of customer needs at the beginning of the process (Davenport and Kudyba, 2016; Blagoeva and Belsoska, 2019), creating value with data, including market feedback loops (Porter and Heppelmann, 2015; Davenport and Kudyba, 2016), digital innovation capabilities as an influencing factor (Edu et al.,

2020) and describing distinct phases in the development process, from the data source to bringing value to the market (Davenport and Kudyba, 2016; Holler et al., 2018).

3.2 Types of contribution

We used a inductive approach to identify four types of contributions in the 19 articles representing the formalisation of IoT NPD in the literature. Most of the articles were associated with processes (10), followed by methods (3), frameworks (4) and architectures (2).

The *processes* proposed in the IoT NPD literature can be divided into technology development process models (Aristodemou et al., 2019), NDP (Cooper, 2010) and a combination of both (Li et al., 2019). We identified iterative technical validation development processes with the primary artifacts in IoT NPD as 'hardware', 'data', 'data presentation', 'system and user feedback', and 'pilots' (Sjöman et al., 2018), as well as descriptions of distinct phases such as 'drafting', 'development' and 'integration' (Lewandowski and Thoben, 2017; Tomiyama et al., 2019). Furthermore, we found a description of how specific phases, e.g., the concept phase (Wilberg et al., 2018) or customer (information use) phase (Thongprasert and Jiamsanguanwong, 2021), can be supported by a process model. In addition to holistic descriptions of processes for IoT NPD (Lee et al., 2020, 2022), we identified specific NPD processes for data product development (Davenport and Kudyba, 2016; Blagoeva and Belsoska, 2019).

Frameworks provide a conceptual view and can be used to describe innovation processes. We identified frameworks that can be divided into a capability view used to implement IoT NPD (Edu et al., 2020), a data-driven view (Cantamessa et al., 2020; Briard et al., 2021) and a management view, which can be used to understand the impact of IoT NPD on business models and consequently the effects on company strategy (Porter and Heppelmann, 2015).

We also revealed *methods* for IoT NPD, which enable us to understand the 'key mechanics of digital product innovation […] addressing different levels of product development to support the early lifecycle stages of digitised products' (Holler et al., 2018). In addition to looking at the whole development process, we identified a description of strategy analysis (Schuh et al., 2019) and the adaptation to concurrent multidisciplinary methods for component-based development (Al-Fedhly and ElMaraghy, 2020).

Architecture describes how technological readiness (Dremel et al., 2020) and the 'level of smartness' (Zhang et al., 2019) affect product development processes in IoT NPD.

3.3 Elements of the data value chain

Addressing RQ2, our review revealed that studies in the literature vary in terms of how they formalise the process of IoT product development. Most of the selected articles lacked a detailed description of data science-driven design and development processes that incorporate data analytics and AI, thus reflecting the missing link between IoT NPD and data science. Consequently, it was unclear which parts of the concept corresponded to which element of the data value chain (Lim et al., 2018). Chain elements were sometimes mentioned in discussions of the required tasks at a general level, and in other cases, the concept treated several elements as one.

None of the investigated works on IoT NPD captured the whole data value chain. The term and topic of 'data source' were mentioned most often (19%). In contrast, the least discussed element of the chain was 'information'. The frequency of appearance for each step is shown in Table 4. Table 5 summarises the main tasks within each process step.

Table 4 Data value chain steps identified in the literature

Process steps	*Definition according to Lim et al. (2018)*	*Frequency*	*Share (%)*
Data source	The object or human to be measured	73	19
Data collection	How the data are collected (e.g., physical sensors, surveys)	24	6
Data	The information content of the data	54	14
Data analysis	The methods, degree of automation and maturity of the data analytics process	75	19
Information	The type of information extracted from data through data analytics.	16	4
Information delivery	How the generated information is delivered	20	5
Customer (information use)	Who uses the generated information, and for what purpose	45	12
Value in information use	How the information user benefits from the generated information.	57	15
Provider network	The partner network must realise the product vision (e.g., sensor manufacturer, data management, software engineering, etc.).	24	6
Total		388	**100**

Table 5 Derived tasks regarding IoT NPD throughout the data value chain

Process step	*Main derived tasks*
Data source	Determination of initial architecture and requirements; sensor feasibility and selection; validation of sensor configuration and hardware
Data collection	Strategy and planning of data collection; definition of the type of data collection; design and development of data sets
Data	Data quality assessment; labelling and validation of data
Data analysis	Definition of analytics component, type and method; model exploration and development; cross-disciplinary data interpretation
Information	Decisions on AI methods; classification; insight and knowledge generation
Information delivery	Definition and evaluation of interaction concepts
Customer (information use)	Identification of customers; identification of (latent) customer requirements; retrieval of market feedback; monitoring of product usage; evaluation of user acceptance
Value in information use	Definition of business value; transformation of customers' needs to a data analytics solution; involvement of the stakeholder in the value creation process
Provider network	Selection of hardware providers; setting up of strategic alliances; assessment of capabilities in terms of implementing the final system; decisions on in-house/outsourcing; data management

Thirteen publications explicitly addressed the process step involving the data source and outlined the importance of the definition of requirements and initial architecture for the system. Our results show that many authors used a prototyping method with different levels of fidelity and proofs of concepts (Davenport and Kudyba, 2016; Sjöman et al., 2018; Holler et al., 2018; Li et al., 2019). Moreover, the approach of the digital twin (Porter and Heppelmann, 2015) to decouple the data source (form) from the data analytics development (function) accommodating unpredictability in the innovation process (Austin et al., 2012) was applied. The articles in the literature recommended several development practices that can be applied when starting IoT NPD since changing the data sources during the project '[increases] the time and cost for project completion' (Lee et al., 2020). Some authors emphasised the importance of designing the most efficient sensor configuration. It is a crucial part of the overall data strategy (Wilberg et al., 2018; Briard et al., 2021), e.g., by considering which data should be gathered and how often they should be analysed (Porter and Heppelmann, 2015). The sensor feasibility and selection dimensions were evaluated in three articles (Lee et al., 2020; Porter and Heppelmann, 2015; Li et al., 2019). The effect of data sources on the subsequent data analytics processes, which define the input data for the machine/deep learning models (Sjöman et al., 2018), was addressed in eight articles.

Furthermore, the studies in the literature highlight the vital link between data quality and value creation. The challenges involve deciding on the data set (simulation or real-world) and appropriate analytics (AI) techniques at various stages of the development process. The assessment of data quality is critical because the information content of the data is directly related to the quality of the end product (Lim et al., 2018). These studies emphasised the strong interdependence between the design of data collection and the design of the analytics components responsible for information quality. In contrast to traditional product development, the use of 'immature' data sets at the start of the development process poses a significant risk: low data quality leads to insufficient or wrong information, making it hard to make decisions or form a consensus (Lim et al., 2020). The methods used to evaluate data quality, labelling and validation may differ depending on the purpose of data collection.

Seven articles addressed the data value chain's 'information' step. The findings imply a high interdependence between data collection design and analytics component design. Particularly in the beginning stages, most of the different process models and methodologies emphasise the need for cross-domain collaboration to develop and evaluate the resulting models (Lewandowski and Thoben, 2017; Lee et al., 2020; Li et al., 2019; Cantamessa et al., 2020; Briard et al., 2021). The arguments made by Porter and Heppelmann (2015); Lewandowski and Thoben (2017) and Cantamessa et al. (2020), and are similar in that they emphasise the task of knowledge generation and gathering deeper insights.

Several different types of interaction were used to test the effectiveness and usability of the provided information (step 6, 'information delivery'). Tomiyama et al. (2019) proposed a classification of interaction types that differentiated between modalities (verbal, haptic, etc.). In contrast, Schuh et al. (2019) and Edu et al. (2020) focused on the communication paths (none, unidirectional and bidirectional) and the related interfaces between humans and the smart product. The usability (Holler et al., 2018) and the need for early testing of pilots with customers were addressed (Porter and Heppelmann, 2015; Sjöman et al., 2018; Zhang et al., 2019; Thongprasert and Jiamsanguanwong, 2021).

Steps 7 and 8 of the data value chain indicate that smart products can create value from a function (related to the physical components) and enhance emotional value (Raff et al., 2020). However, value is only created when customers (i.e., information users) accept the technology (Thongprasert and Jiamsanguanwong, 2021) and use the information by applying it within the process (Lim et al., 2018). Therefore, Lee et al. (2020) emphasised considering the goal and purpose of information use in IoT NPD to reduce invention risk in smart product development. The effective use of data, regardless of its source or format, remains a significant barrier (Cantamessa et al., 2020) and hence knowledge about the inherent business and user value is crucial, particularly at the very beginning of development (Holler et al., 2018; Briard et al., 2021). Establishing the link between which data is relevant for generating the expected value (i.e., information) was essential (Wilberg et al., 2018). Identifying customers' latent requirements poses another challenge at the data product development stage. Creating poorly defined, contradictory or unrealisable requirements (Lee et al., 2020) leads to ineffective or inefficient product development processes (Tomiyama et al., 2019). Coordinating the investigation of customer needs while validating current product features is another critical issue in product development iterations (Cantamessa et al., 2020).

The results reveal that data product development changes the NPD process at the network provider stage (Step 9) and expands the array of roles and competencies involved. In this context, the literature reveals the importance of addressing dynamic capabilities in NPD, as companies aiming to develop IoT products need to establish IoT resources and capabilities (Edu et al., 2020). Building up strategic alliances and importing and coordinating resources were discussed concerning the involvement of diverse stakeholders (Li et al., 2019; Lee et al., 2020; Thongprasert and Jiamsanguanwong, 2021). Most of the authors emphasised the topic of in-house sourcing versus outsourcing (Porter and Heppelmann, 2015; Cantamessa et al., 2020). More specifically, data management was a critical element of the capability to implement smart product development. The authors discussed data infrastructure (Li et al., 2019) and the efficient exchange, processing and sharing of data (Edu et al., 2020).

3.4 Synthesis of critical success factors

In summary, our literature synthesis helped explain the nature of data product development issues and the different steps of the data value chain. Deriving success factors is another approach to exploring phenomena and understanding IoT NPD incorporation with data science. Although NPD literature has explored (Florén et al., 2018) and evaluated (Aristodemou et al., 2020), success factors in the FEI of NPD in the specific context of data-intensive IoT product development have gained less attention. Our analysis of the tasks associated with each step in the data value chain (see Table 5) has shown several sources of fuzziness that characterise IoT NPD. Thus, identification of the potential sources of uncertainty in IoT NPD is crucial. The critical factors identified are summarised in Table 6.

Table 6 Critical success factors in IoT NPD identified based on the data value chain

Process steps	*Factor*	*Key metrics*	*Examples of tools and techniques*
Data source	The maturity level of the data source Definition of requirements User acceptance	Number of changes to data sources Development/integration time	Technology assessment Proof of concept Feasibility testing
Data collection	Strategy and planning of data collection	Number of data sets The efficiency of data collection	Data design thinking
Data	Data quality	Degree of achievement of defined data quality criteria Pre-processing time	Data quality assessment Validation
Data analysis	Maturity of the data analytics process	Number of analytical concepts Effective use of collected data	Data science methods (machine learning, deep learning, etc.)
Information	Transformation of implicit to explicit knowledge Subjective data interpretation	Number of insights (e.g., patterns, explicit database)	Classification, knowledge generation methods Stakeholder workshops to discuss information outcomes
Information delivery	Product efficiency and acceptability	Number of interactions with customers, number of pilot studies	Different data interaction modalities, usability tests
Customer (information use)	Know-how about customer needs, acceptance and market	Several (latent) customer requirements, several examined customer needs, and acceptance metrics (e.g., perceived ease-of-use, usefulness, privacy, etc.)	Users need studies, user acceptance studies, product usage studies
Value in information use	Defined business value	Number of suitable use cases, number of customers involved in the value creation process	Idea generation, business value canvas, data-driven design
Provider network	IoT capabilities	Number of strategic alliances with partners, percentage of in-house/outsourcing capabilities	Innovation ecosystems, data management

The research perspectives, types of contributions and adherence to the data value chain were investigated in this study. In addition, based on our literature synthesis for answering RQ1 and RQ2, we identified factors influencing the FEI within each step of the data-intensive IoT NPD.

4 Discussion

Our initial assumption was that data-driven IoT NPD is worth considering on its own due to its complexity that stems from its multi-disciplinarity and the low TRLs in both, the cyber and the physical, parts of the new product. The goal of the review was to investigate the extent to which data-intensive IoT NPD is already covered in existing IoT NPD literature.

The top three topics, namely ‘data source’, ‘data analysis’, and ‘value in information use’, received the majority of the attention in IoT NPD literature (together 53% of all appearances, see Table 4). These can be considered the tentpole topics of data exploitation, as they represent the essential data-to-value process. However, this view is simpler than our understanding of data-intensive IoT NPD. The ‘provider network’ topic, which contains the building of multi-disciplinary product design capabilities that is essential to data-intensive IoT NPD, only received little attention (6%). Equally small is the share of the topics ‘data collection’ and ‘information’ (6% and 4%), which are concerned with planning, conceptualising and modeling the data analytics process. Advances in this area could help reduce risks by providing tools to make assumptions and hypotheses about the product’s realisation explicit and to regularly check their validity. Finally, the topic ‘information delivery’ had a share of 5%. However, it is covered extensively in its fields of research like Human-Computer Interaction (HCI) and the data visualisation research community.

Concept development in data-intensive IoT NPD is still in its infancy. Our results show that there is no comprehensive IoT NPD process model that considers all aspects of the data value chain, let alone the increased effort from orchestrating multi-disciplinary teams in data-intensive IoT NPD. An analysis of the examined research perspectives showed that the literature mainly described observed phenomena and provided frameworks or typologies followed by proposing descriptive processes for specific steps of the data value chain. Although these approaches may be used in practice, they lack the detail and precision required to apply a prescriptive model (Cooper, 1983). Thus, a theoretically guided process model that can guide managers of IoT NPD is not available yet. Consequently, to provide a basis for proposing such a prescriptive model, we must determine the requirements of an ideal IoT NPD process model.

4.1 Towards requirements for an IoT NPD process model

In general, technology development projects should follow a process design (Cooper, 2007), and the technological feasibility should be proven (Koen et al., 2014) for a stop/go gate decision leading to NPD. A defined process that supports transparency and a shared understanding of this highly interdisciplinary process is needed (Gassmann and Schweitzer, 2014). Davenport and Kudyba (2016) and Cantamessa et al. (2020) already developed a comprehensive understanding of a data product development process. Nevertheless, a standardised knowledge process for the very early stages of innovation that ensures consistency and convergence between the sensor data source and the expected data value, as well as the collection and analysis of the right sets of data for meaningful decisions, has yet to be proposed (Cantamessa et al., 2020). Hence, a process model that can bridge the gap between existing IoT NPD approaches and the implementation of the data value chain by structuring the design phase (i.e., the FEI for data-intensive product development) would be helpful. The studies in the literature support this conclusion; moreover, Reit (2021) pointed out that innovation success lies not only in the generation of creative ideas but in their implementation. In a first step toward the realisation of a normative IoT NPD process model, we have therefore derived requirements that could illustrate a solution.

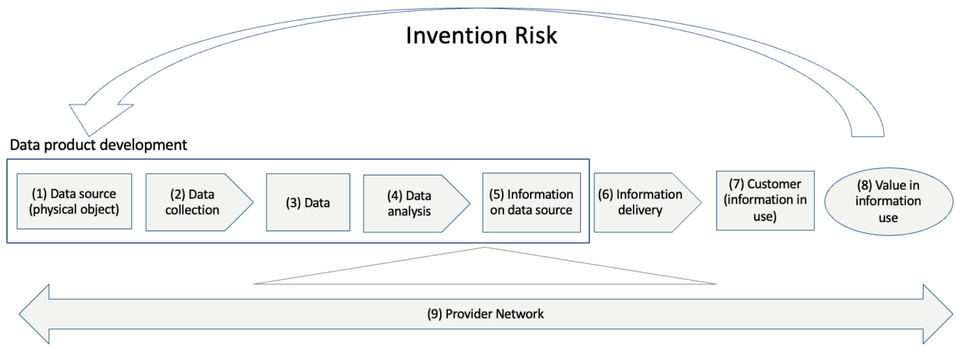
4.1.1 Requirement 1: consideration of contextual specificity of data science

Many process models, methods and tools for NPD in the FEI have already been developed and examined (Gassmann and Schweitzer, 2014; Cooper and Fürst, 2020). While the literature on IoT NPD emphasises the technical assessment phase, there is still a gap in proposing a process model that includes specific steps for data science. This observation is supported by Kayser et al. (2018), who highlight the challenge of creating data analytics processes for IoT product development. Although some recent articles have focused on the complexity of IoT NPD (Lee et al., 2020; Cooper and Fürst, 2020), they did not offer prescriptive knowledge on how to manage it better. Almost none of the process models or proposed approaches specifically supported data product development within the process. Ultimately, descriptive knowledge to guide managers (Cooper, 1983) in building complex data analytics products is still the missing link. The literature suffers due to the nature of various research perspectives explained in Subsection 3.1. In summary, IoT NPD is characterised by prescriptive process know-how and a normative model formalising the process for data-intensive IoT NPD still needs to be recommended.

4.1.2 Requirement 2: non-linearity

Although there is a theoretical notion that NPD processes are generally sequential, there is increasing debate over moving from linear to flexible models (Marzi et al., 2021). For IoT NPD, iterations and agile structures must create successful sub-artifacts to a final data-intensive IoT product. This observation was also reflected in the results of the review. This is especially true for the ‘curation’ phase, i.e., the phase of evaluating and integrating the data from various data sources, which is accompanied by knowledge building through theory, experiments or simulations. In other words: is there sufficient information in the data to answer the desired business value question? To answer this question, data engineers and scientists need to constantly perform data design iteration loops by reviewing the problem (value question), the data sources and the results (Li et al., 2019), which are not known *a priori* when ‘exploring the data’ (Saltz, 2015). Owing these ‘unknown unknowns’ or ‘black box activities’ (McCarthy et al., 2006), unpredictable conflicts occur at different stages and times, leading to continuous learning and improvement.

Figure 4 Adapted illustration of the data value chain (Lim et al., 2018)



Arising from the non-linear properties of IoT NPD, a process model should support product managers not only to moderate the known options with existing solutions but also to manage unknown options that require novel solutions (Marzi et al., 2021).

4.1.3 Requirement 3: linking technical complexity with social complexity

Based on the evidence in the literature (Urbinati et al., 2019), we assume that a peak in the number of emerging topics relating to solving data value conflicts occurs in the transformation from the value proposition to data source assessment as well as in the curation of the data valid for answering the value question. Thus, by raising awareness of the issues emerging in NPD (Kallenborn and Täube, 2014), an explicit link between the technical complexity arising from the steps of the data value chain and the knowledge discovery process should be considered. In terms of 'data-intensive scientific discovery theory' (Hey, 2012), what leads to knowledge advancement is the translation of learned patterns into interpretable hypotheses (Karpatne et al., 2017). Additionally, the proposed process model should make it possible to link technical complexity with the different actors associated with data product development (social complexity) to solve emergent issues. Since IoT NPD follows a complex system development process (Ulrich et al., 2020) characterised by highly parallel processes for system-level issues and stop/go gate decisions, a prescriptive IoT NPD process model should consider the dynamics of socio-technical complex adaptive systems (Kallenborn and Täube, 2014), too.

4.1.4 Requirement 4: the impact of data quality on the value question

Recent work (Machchhar et al., 2022) has confirmed that the data collection phase has not been sufficiently considered in the development process of smart products. One major challenge is the proper design of data volumes and formats; this was revealed in the review, e.g., by Cantamessa et al. (2020), who highlighted that the 'definition of the right level of observation width to avoid data overwhelming and to generate the right information for innovation opportunities' is a central aspect within early stages of data product development. To reduce this uncertainty factor in IoT NPD, a prescriptive IoT NPD process model should allow for continuously aligning data quality requirements with the final innovation outcome. Data quality dimensions beyond accuracy should be considered, such as those proposed by Wang and Strong (1996). On the other hand, Wirth and Wirth (2017) emphasised not overstating resource constraints and technical feasibility in the early stages. At this moment, the method of prototyping or proofs of concept is predominantly described as decoupling the data source (form) from data analytics development (function), which should be considered in a normative process model to reduce unpredictability in the innovation process (Austin et al., 2012).

4.1.5 Requirement 5: IoT capabilities

The characteristics of IoT NPD, such as technological creation and iterative adoption of artefacts (Lee et al., 2020), reflect the value placed on knowledge from both, which is 'developed inside the firms and absorbed outside of firms' boundaries' (Filippetti, 2011). It leads to an appropriate assessment of IoT resources and capabilities to support value creation toward technology deployment (Edu et al., 2020). The need to integrate sources of knowledge for enhancing the success of NPD processes is reflected in the increasing amount of research over the last few years (Marzi et al., 2021). Nevertheless, while the studies in the literature emphasise that stakeholders play a crucial role in the NPD process and in creating shared value (Machchhar et al., 2022), there has been less research into which stages are involved and how to foster collaboration with suppliers (Marzi et al., 2021). Notably, in the beginning, most of the different approaches reviewed here emphasise the necessity of cross-domain cooperation when designing and evaluating the resulting models. At this moment, a prescriptive IoT NPD process model should allow understanding and considering NPD dynamics, e.g., through the lens of the theory of digital capabilities for digital innovations (Wiesböck and Hess, 2018).

4.2 Direction for future work

The results of this work help to understand and investigate NPD dynamics from the perspective of the data value chain (Li et al., 2019) emerging in NPD (Marzi et al., 2021). By proposing requirements and considering the literature review results based on the identified critical factors, we can create a coherent framework and a shared understanding of IoT NPD. The innovation outcome may be either a smart product (Porter and Heppelmann 2015), a smart service (Götz et al., 2018), or even a physical product enhanced through a data-informed product design (Pavliscak, 2015). Still, the complexity of handling the IoT aspect remains the same. To enable fruitful research into the incorporation of Data Science into IoT NPD, it is important to ensure that data mining processes are conceptualised and defined within NPD. As a next step the outcomes of this work are intended to be instrumental in research into the design of a normative process model to structure IoT NPD based on a reference model (Lim et al., 2018) that considers the comprehensive lens from data source to value creation. The ability of such a model to outline the concept of IoT NPD incorporating Data Science could provide a basis for further research work and extend recent proposals for managing smart product development (e.g., Huikkola et al., 2021).

The proposed framework can respond to recent calls for empirical digital innovation research (Nambisan et al., 2017; Briard et al., 2021) with data-intensive IoT NPD processes serving as the unit of analysis. In this way, the characteristics of IoT NPD, their development practices and the context in companies can be studied. For example, applications in human motion analytics could be selected (sports, fitness and well-being, digital health and prevention, media). Data-intensive IoT NPD is typically established as best practice in these industries (e.g., the wearables sector). Moreover, these domains are inherently well-suited to data-intensive scientific discovery (Tolle et al., 2011). The domain of medical monitoring may be another field of application, as the requirements for developing a medical data product are fundamentally different from those for non-medical data products (e.g., regulations, data protection). Owing the diversity of applications of IoT NPD and the associated requirements, we assume that there is no one ultimate process model for IoT NPD. On the contrary, depending on the maturity level (Kayser et al., 2018), there will be different manifestations or pathways, as already discussed by Holler et al. (2018) and Hunke et al. (2020a, 2020b).

Exploiting smart product development processes not only involves looking at technical aspects. It requires an understanding of the links between the multiple persons involved and their relationships to the various aspects of creating value out of data, particularly the development of data analytics capabilities and the associated impacts on development risks (e.g., costs, invention). Thus, the data and consequently the information quality requirements (Wang and Strong, 1996) impact the final innovation outcome and also the sub-artefacts created on the way to IoT NPD; this requires an understanding of each of the roles in the data product development process, which are often ambiguous, complex and heterogeneous. We, therefore, assume that the challenges and possible solutions for data-intensive IoT NPD can be categorised based on the level or function at which they emerge, classified by De Mauro et al. (2018) as business analysts, data scientists, developers and system managers. A systematic analysis of the activities in data-intensive IoT NPD based on the different actors' perspectives can help understand these network activities in more detail.

5 Conclusion, limitations and recommendations for future work

The research focused on IoT NPD literature is scattered into various subdomains. Therefore, this study aims to provide a thorough overview and discussion of current academic research streams in the emerging field of IoT NPD and to provide a structure for further research in this area. In this study, academic literature on IoT NPD was reviewed and reflected in three categories: 1) geography of literature, 2) types of contributions and 3) formalisation of literature based on steps for developing a data-intensive IoT product according to the data value chain (Lim et al., 2018). Studies in the relevant literature have distinctive contributions (models, frameworks, taxonomies), different research perspectives (design, product development, product innovation) and differ in the depth of implementation process elements of the data value chain. Based on the identified and success factors proposed to be considered in the early stages of IoT NPD, we retrieved requirements that may serve as a base to offer a process model for data-intensive IoT NPD.

Few approaches exist for integrating data science into IoT NPD in current management theory and practice. While there has been a substantial discussion on the nature of NPD (Aristodemou et al., 2019), literature on IoT NPD is still not fully explored. Thus, the proposed process model is in the early stage. Like 'smart products' (Raff et al., 2020), a similar challenge for IoT NPD. This is also reflected in the numerous publications in various journals from different disciplines, showing that research on IoT NPD generates interest from different perspectives. Indeed, when conducting the literature review, data extraction proved difficult due to the variety of disciplines involved and the inconsistencies in reporting the approaches. It was noticeable that despite querying relevant scientific databases and focused keyword searches, relatively few NPD concepts could be identified that specifically targeted the NPD process in IoT. This may be due to the contextual specificities of IoT and data science, for which the search results were unrelated to technology and innovation management. Our review found that data-intensive IoT NPD is only partially covered by existing IoT NPD literature. Nevertheless, it indicates that the topic of data-intensive product development is an emerging discipline.

We argue that the present literature lacks normative process models but offers actual practice without guaranteeing that this practice is ideal and can serve as a guide for others (Cooper, 1983). We identified many guidelines for designing data-driven product development in the context of IoT. However, most articles do not consider the integration of data analytics and the building of IoT capabilities and resources from a management perspective. Although digital-physical product development (Hendler and Boer, 2019) and IoT NPD have received some attention in the literature, only a few approaches comprehensively incorporate data analytics process models into NPD (e.g., Li et al., 2019; Lee et al., 2022).

Five main requirements emerged from the literature review in the identified research areas and the proposed critical success factors. First, a normative process model for structuring IoT NPD is missing and must be addressed. Second, the non-linear characteristics of IoT NPD need to be further emphasised. Third, a prescriptive IoT NPD process model should consider the dynamics between technical and social complexity, i.e., job roles involved in IoT NPD. Fourth, data quality dimensions beyond accuracy need to be addressed, considering the impact of data quality on the final value achieved within the targeted business case. Fifth, the assessment of IoT resources and capabilities to support value creation and advance toward technology deployment need to be further emphasised.

From a managerial view, the efficiency of data analysis processes is essential for companies driving digital transformation. Product managers must understand how to turn data into value. Consequently, the steps from data source to value need to be considered for customer-centric IoT NPD; our discussion indicated the need for theory development to deal with the interdisciplinary management of IoT innovations involving Data Science. The findings highlight factors that need to be considered within the FEI for early decision-making and idea generation in data-intensive IoT product development. Moreover, this work provides a comprehensive understanding of the emerging paradigms in NPD with data-driven capabilities, which can help practitioners manage the complexity of AI innovation, including sensors. It will support managers in succeeding in the early stages of IoT NPD by allowing them to be aware of the contextual specificities of data science. Furthermore, applying a deductive approach can identify the discriminating factors associated with IoT NPD.

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