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Improving Business Processes with the Internet of Things - A Taxonomy of IIoT Applications

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IMPROVING BUSINESS PROCESSES WITH THE INTERNET OF THINGS - A TAXONOMY OF IIOT APPLICATIONS

Research Paper

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Abstract

The Industrial Internet of Things (IIoT) paradigm constitutes the connection of uniquely identifiable things to the internet in an industrial context. It provides disruptive capabilities and value propositions, especially for the management and improvement of business processes. To exploit these, many companies have already implemented manifold IIoT applications along their value chain activities aiming at beneficial Business Process Improvements (BPI). However, research on IIoT-based BPI is low on theoretical insights. To add to the descriptive knowledge of the IIoT, a structured synoptic view and classification scheme are required. The work at hand addresses this need by providing a taxonomy of IIoT-based BPI applications. Based on the combination of an inductive and deductive research methodology, the created taxonomy consists of six dimensions, seven subdimensions, and 40 characteristics. The taxonomy is evaluated on a sample of 30 IIoT applications from the literature and 10 real-life applications from a market-leading company.

Keywords: Industrial Internet of Things, Business Process Improvement, Business Process Management, Taxonomy

1 Introduction

In the last three decades Internet of Things (IoT) applications have spread massively in all areas of private and professional life, summing up to at least 43 billion IoT devices by 2023 (Dahlqvis et al., 2019). The connection of uniquely identifiable things to the internet by equipping all kinds of objects with sensors and actuators provides disruptive innovations for the private, public, and industrial sectors (Atzori et al., 2010). The IoT, therefore, bridges the gap between the physical and the digital world enabling the integration of objects into the networked society. Furthermore, a paradigm denoted as the Industrial Internet of Things (IIoT) has evolved that leverages the IoT, albeit transcending the concept of the *thing* toward industrial applications. In contrast to the IoT comprising various applications, e.g., smart home or smart city, the IIoT constitutes an explicit use of IoT technologies within industrial organizations and applications. Increasing connectivity between virtually every animate and inanimate entity within industrial processes creates a complex network of communication and interaction (Langley et al., 2021). In this context, the IIoT comprises people, data, processes, and things while information is turned into actions, creating new capabilities, richer experiences, and unparalleled economic opportunities (Azam et al., 2016). Thus, IIoT applications are projected to provide extensive benefits based on their technological capabilities and the underlying business process details (Langley et al., 2021), while the primary value drivers include both cost-cutting and revenue-raising impacts (Demirkan et al., 2015). Organizations that adapt their extant business models and business processes to these new technological possibilities have considerable opportunities to innovate and are potentially highly competitive. Hence, it is important to understand, how beneficial Business Process Improvements (BPI) can be achieved. This is important from a theoretical and a practical point of view as the combination of both fields IIoT and BPI is only sparsely addressed in current research (Stoiber and Schönig, 2021). No existing models sufficiently describe the dimensions and characteristics of IIoT applications with the goal of beneficial BPIs. This lack of knowledge constitutes a barrier for properly understanding the convergence of IIoT and BPI and advancing it for the beneficial transfer to practical use. Against this backdrop, we close the existing research gap by formulating and eventually addressing the following research question (RQ):

RQ: *How can IIoT applications aiming at Business Process Improvements be classified in terms of their essential characteristics?*

We present a conceptual taxonomy of IIoT-based BPI applications to address this research question. In this regard, we define the term "IIoT-based BPI application" as the purposeful use of IIoT technology within an industrial process to improve the same concerning predefined objectives. This includes a wide range of applications, e.g., tracking and tracing of process entities using simple RFID tags, or complex automation of formerly manual process activities using combinations of sensors and actuators. The taxonomy has been developed according to the systematic method of Kundisch et al. (2021) that reasonably extends the proven procedure of Nickerson et al. (2013) by adding supplementary steps. As this method follows principles of the Design Science Research (DSR) methodology (Hevner et al., 2004), the final taxonomy has been rigorously designed as a DSR artifact. For the taxonomy, we mainly focused on value-adding processes and activities within industrial organizations which are crucial for creating competitive advantage. For these primary value chain activities, the IIoT has the greatest leverage to generate value (Sisinni et al., 2018). To evaluate the usefulness of the taxonomy, we performed a classification of 30 literature and 10 real-life applications, and an expert survey.

The contribution of the taxonomy consists of two parts. First, it connects the research fields of IIoT and BPM and, therefore, extends and advances existing knowledge on both topics. The taxonomy constitutes the first structured and systematic classification tool of IIoT-based BPI and gives an overview of relevant elements and possible manifestations of IIoT-based BPI applications. Thus, it enables researchers to describe, understand, and analyze the phenomenon and create a starting point for further research (Nickerson et al., 2013). Second, it supports practitioners with the cognitive process of classifying already existing and possible future IIoT-based BPI applications. This leads to an improved analysis of the IIoT's potential. Decision-makers are able to perform an in-depth analysis of applications and get an impression of relevant elements and influencing factors to effectively select and implement IIoT-based BPI applications.

The remainder of this article is structured as follows. In section 2 we illustrate the theoretical background of the IIoT and its value propositions for business processes. Moreover, already existing taxonomies regarding IoT, IIoT, and Business Process Management (BPM) are presented to illustrate past and current research. In section 3, the applied research methodology of Kundisch et al. (2013) is described, while its application is illustrated in section 4. Subsequent, in section 5 the final taxonomy of IIoT-based BPI applications is presented in detail. We conclude with a general discussion of the final taxonomy, its limitations, and potential future research in section 6.

2 Theoretical Background and Related Work

2.1 IIoT meets Business Process Improvement

There are dozens of different approaches for defining the term IoT, its components, features and capabilities, and the *thing* itself. The Institute of Electrical and Electronics Engineers (IEEE) tried to combine several different descriptions toward a universal definition. According to the IEEE, the IoT is a network that connects uniquely identifiable things to the internet. Through the exploitation of unique identification and sensing, information about the thing can be collected and the state can be changed from anywhere, anytime, by anything (Minerva et al., 2015). Therefore, the term *things* corresponds to the idea of creating a ubiquitous presence of objects equipped with sensors, actuators, or tags. On the other side, the term *internet* refers to the ability of these things to build a network of interconnected objects based on several specific network technologies. These two perspectives can be complemented by a semantic view, which represents the ability of IoT to uniquely identify things and store, process, and exchange data (Atzori et al., 2010). While the IoT has the potential to create or transform products, services, and business models, its capabilities have also a disruptive impact on business processes (Leminen et al., 2018). In line with the growing share of industrial IoT applications, a more specified paradigm has been developed, called the Industrial IoT (IIoT). In contrast to the generic definition of IoT, the IIoT constitutes the use of certain IoT technologies, e.g., certain kinds of smart objects within cyber-physical systems, in an industrial setting, to promote goals distinctive to industry. The IIoT, therefore, differentiates itself from the IoT by the purposes to which the technologies are put (Boyes et al., 2018). Current research and already implemented applications clearly show that IIoT reveals many extensive possibilities for improving business processes. This is highly relevant as many companies follow a process-oriented view of their organization and all including operations (Porter, 1985). In this context, especially redesigning and improving business processes is a highly relevant topic in both research and the business environment and is considered one of "the most important and common titles in both literature and applications" (Coskun et al., 2008). BPI, in this context, is part of the Business Process Management (BPM) discipline, which is responsible for identifying, discovering, analyzing, redesigning and improving, implementing, and monitoring business processes (Dumas et al. 2018).

2.2 Taxonomies in IoT and BPM Research

Contributing to the theoretical and practical insights of IoT and IIoT, several white papers, case studies, technical articles, and classifications have been proposed. Here, especially classifications provide theoretical insights on inner correlations, characteristics, and relations of the phenomena. A classification, reduced to its mere definition, enables the arrangement of a set of entities into distinct groups, dimensions, and characteristics (Bailey, 1994). Therefore, classifications enable researchers and practitioners to understand, analyze, and structure the knowledge within a distinct field (Nickerson et al., 2013). Classifications come in different forms, e.g., frameworks, typologies, ontologies, or taxonomies, which are often used interchangeably. Among them, taxonomies, defined as an empirically or conceptually derived system of groupings of objects, have proved to be particularly useful within information system (IS) research (Glass and Vessey, 1995), given the speed of sociotechnical progress that requires continuous efforts of understanding. Regarding IoT and IIoT, researchers have already created a multitude of taxonomies that address different facets of both phenomena.

As IoT and IIoT technology enables novel business models, a classification scheme to further analyze its potential is of high importance. Woroch and Strobel (2021) and Hodapp et al. (2019) addressed this topic by creating a taxonomy of IoT-enabled business models. Regarding the technical specifications of the IoT system, several taxonomies focused on characteristics on a device level, e.g., Dorsemaine et al. (2015). This includes characteristics of the types of used sensors, e.g., motion, position, pressure, communication protocols, functional attributes, or software resources. While this does not provide any information about the actual role of the IoT device, an IoT stack-centric taxonomy allows further classification dimensions (Püschel et al., 2016). By classifying an IoT or IIoT application according to established layer architectures and IoT stacks that also include the application and service layer, the role of the application can be defined. Also, a taxonomy on the socio-material perspective of the IoT has been developed that focuses on business-to-thing interactions (Oberländer et al., 2018). However, this does not allow to draw any conclusion about the business objectives that are associated with the IoT application. In this respect, Yaqoob et al. (2017) have developed an IoT architecture taxonomy that combines a mixture of business architecture and technical characteristics, also including business objectives and enabling technologies of IoT. However, lacking a specific view on IIoT applications, it has limited value for classifying these kinds of applications. Against this, Schneider (2017) developed a taxonomy of IIoT which focuses on industrial applications. But only consisting of six characteristics, it does not provide a useful tool for a detailed classification. Finally, Boyes et al. (2018) merged all the stated taxonomies with their different viewpoints to develop an analysis framework for IIoT that enumerates and characterizes IIoT devices. Certainly, without providing any characteristics that allow the classification considering business processes, it does not serve to address the formulated research question. While some taxonomies address BPM cases (vom Brocke and Mendling, 2017), business processes (Regev et al., 2006), and options for BPI (Falk et al., 2013), they collectively lack connections to the IIoT paradigm. Having analyzed existing research, we target to fill the identified research gap and address the formulated research question.

3 Research Method

To develop the taxonomy of IIoT-based BPI applications, we applied the extended taxonomy design process (ETDP) by Kundisch et al. (2021). This design process is based on the proven method for taxonomy design in IS research by Nickerson et al. (2013) which has been applied by approximately two-thirds of all IS taxonomies since 2013 (Kundisch et al. 2021). Despite being the de facto standard for the design of IS taxonomies, it lacks transparency for reporting relevant design decisions and guidance regarding taxonomy evaluation. Providing additional design and evaluation steps, the ETDP tackles these issues and constitutes an improved procedure. The ETDP comprises 18 steps and is organized along with the six DSR methodology activities stated by Peffers et al. (2007). In steps 1 to 3, the observed phenomenon (Step 1), the target user groups(s) (Step 2), and the intended purpose(s) (Step 3) of the taxonomy are specified. Further, in step 4, the meta-characteristics are formulated, which define the angle a taxonomy takes on the phenomenon under consideration. As the ETDP is iterative, ending conditions and evaluation goals must be determined in step 5, before the actual artifact creation. These conditions can be both subjective and objective and have a significant influence on the created taxonomy. The actual iterative development procedure starts by choosing the development approach in step 6. Researchers must select either an inductive/empirical-to-conceptual or a deductive/conceptual-to-empirical approach. The selection of the initial approach depends on the availability of data and the researchers' knowledge of the relevant domain (Nickerson et al., 2013). In choosing an empirical-to-conceptual approach, real-life objects are identified first (Step 7e), and dimensions and characteristics are identified (Step 8e) and grouped (Step 9e) subsequently. Selecting the conceptual-to-empirical approach, the taxonomy's dimensions and characteristics are conceptualized first (Step 7c), and real-life objects are mapped to the dimensions and characteristics second (Step 8c). Hereafter, the current taxonomy draft is created or revised (Step 10) and mapped with the formulated objective (Step 11 and 12) and subjective (Step 13 and 14) ending conditions. If all ending conditions have been met, the next step can be reached, else wise, a new iteration starts. Having met all ending conditions, steps 15 and 16 support assessing the conditions of the taxonomy evaluation. This implies adequately configuring an evaluation (Step 15) and performing it (Step 16). In step 17, an *ex-post* evaluation in light of the evaluation goals must be performed to decide, if the taxonomy requires further adaption. If the taxonomy proves to be useful within the evaluation, it must be reported in a manner that fits the purpose and target user groups (Szopinski et al., 2020) (Step 18). To support the taxonomy creation, Kundisch et al. proposed 26 operational taxonomy design recommendations, that we also considered.

In section 4, the application of the outlined ETDP is described to develop the taxonomy of IIoT-based BPI applications. This comprises the problem identification and objective definition (Steps 1 to 5), the actual design, development, and demonstration (Steps 6 to 10), and the evaluation (Steps 11 to 17). The communication and presentation (Step 18) of the final taxonomy are performed in section 5.

4 Taxonomy Design Approach

4.1 Problem Identification and Objective Definition

The theoretical background of IIoT and BPM, respectively BPI, have been discussed in sections 1 and 2. At the same time, we outlined the need for a taxonomy of IIoT-based BPI applications, as no existing taxonomy enables a sufficient conceptualization of this phenomenon. We designed the taxonomy for researchers in the fields of IIoT, BPM, and IS in general. In addition, industrial experts related to IIoT technology and BPM, as well as managerial decision-makers may benefit from our contribution. The purpose of the taxonomy is to identify and structure the characteristics of IIoT-based BPI applications and their relationships. This may enable researchers to further study this field and practitioners to gain insights into potential applications. We define IIoT applications as enablers to improve business processes by either tackling existing challenges or enabling opportunities. Therefore, the development procedure is based on the meta characteristics:

Characteristics of IIoT applications embedded in business processes aiming at beneficial Business Process Improvements.

As objective conditions, we selected the following: *i)* at least one object is classified under every characteristic of every dimension *ii)* every dimension is unique and not repeated, *iii)* every characteristic is unique within its dimension, and *iv)* no new dimensions or characteristics were added in the last iteration (Nickerson et al., 2013). In addition, as subjective ending conditions, the authors must agree that the taxonomy is concise, robust, comprehensive, extendible, and explanatory. These conditions constitute criteria for the *ex-ante* evaluation. Further, a rigorous taxonomy design requires conformity with formulated goals after the *ex-post* evaluation. These goals are, that the taxonomy must enable users to *i)* describe, *ii)* classify, and *iii)* analyze the phenomenon of IIoT-based BPI applications.

4.2 Design, Development, and Demonstration

After initializing the design procedure, we performed four iterations including two inductive and two deductive approaches. Figure 1 illustrates these iterations by stating the selected approaches, the used information sources and methods to perform a conceptualization, and the identified dimensions. After four iterations, no additional knowledge could be generated wherefore the procedure ended.

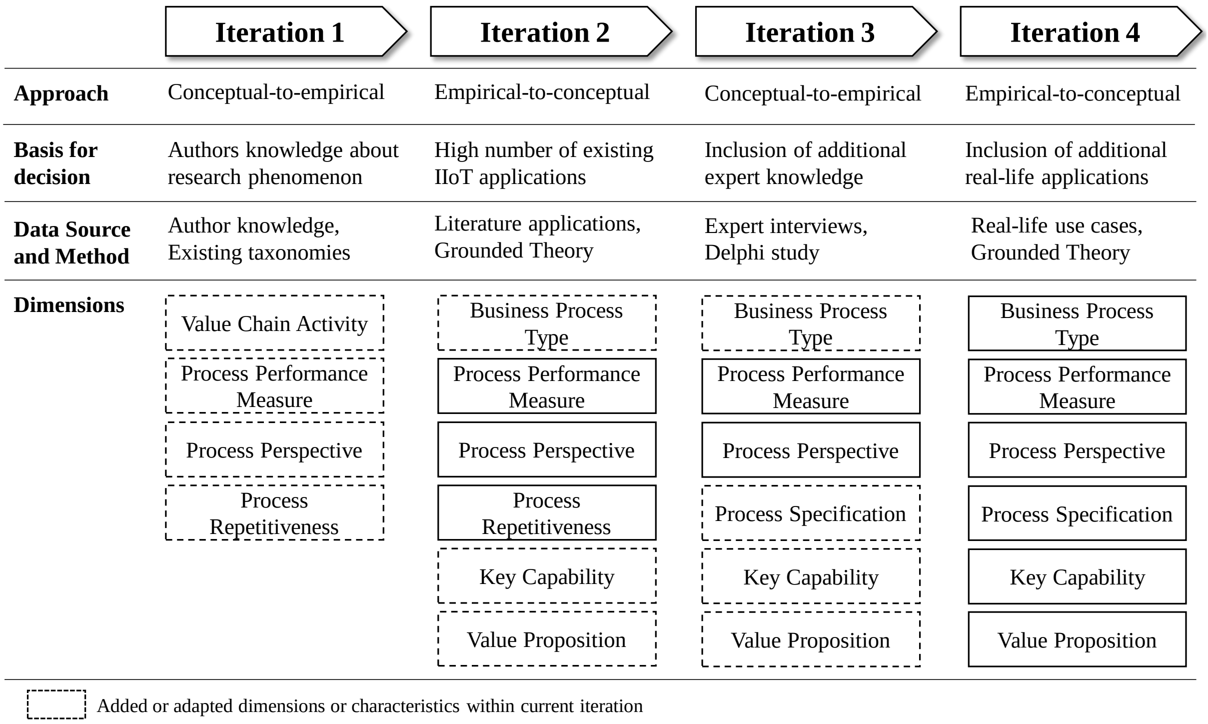

Figure 1. Design iterations.

Iteration 1. We have selected the conceptual-to-empirical approach for the first iteration, as the authors' knowledge holds relevant insights about the phenomenon under consideration. To integrate an even broader knowledge base, we also accounted for and referred to existing IoT, IIoT, and BPM taxonomies. Analyzing IIoT applications at the highest level, we conclude that it is possible to classify them according to their application area within the industrial value chain. We defined the first dimension as *value chain activity* and the primary activities as characteristics (Porter, 1985). Further, specific Process Performance Measures (PPMs) are used to quantify the degree of BPI, which can take different forms. We added *process performance measure* as a dimension including the characteristics defined by Dumas et al. (2018). As different IIoT applications do not uniformly address all facets of business processes, it is essential to define, which perspectives of the process are influenced most. We, therefore, added the dimension *process perspective*, proposed by Jablonski et al. (1996) and Schönig et al. (2014) including the stated characteristics. Finally, we formulated *process repetitiveness* as a binary dimension to specifiy the underlying process type. For IIoT applications, it is highly relevant, if the process and all included data sets and activities are repetitive, or if the IIoT system needs to adapt to varying environments (Benešová et al., 2019). We have identified several literature IIoT applications that can be mapped to the created dimensions and characteristics. The taxonomy T_1 consisted of four dimensions and 17 characteristics. Since this has been the first iteration, the procedure continued.

Iteration 2. For the second iteration, we have selected the empirical-to-conceptual approach as a significant number of objects are available to represent the phenomenon under consideration. To identify a subset of objects, we performed a Systematic Literature Review (SLR) on IIoT applications within business processes. The SLR followed the established procedure proposed by vom Brocke et al. (2009). To improve the structure of the literature search, it has been conducted according to the PRISMA statement (Liberati et al, 2009). At first, the search string *("IIoT" OR "IoT" OR "CPS") AND ("BPI" OR "Process Improvement" OR "Process Optimi?ation" OR "Application"),* as well as the written-out forms have been formulated. We queried the most relevant databases of the underlying research fields, including ACM Digital Library (81 hits), AISeL (132 hits), IEEE Xplore (334 hits), ScienceDirect (238 hits), Scopus (133 hits), and Springer Link (353 hits). To reduce the number of records, three eligibility criteria have been formulated that define, if an article is appropriate for the anticipated purpose. We defined the eligibility criteria as *i)* topicality, *ii)* relevance, and *iii)* credibility. The criteria are translated by only considering peer-reviewed articles with a publication date after 2014 and at least 50 citations. After excluding 546 duplicates and 539 records according to the formulated criteria, we analyzed 186 full-text publications. Eventually, we excluded another 80 publications due to lacking IIoT implementations or BPI references. Moreover, we excluded 25 further publications because of redundancies. This means, that an IIoT application described in a publication is very similar to at least another one and does not provide additional information. The remaining 81 eligible publications have been investigated using the grounded theory. The grounded theory is a qualitative research method that seeks to develop a theory that is grounded in data systematically gathered and analyzed (Urquhart et al., 2010). Especially in IS research, it has proved to be extremely useful in developing context-based descriptions and explanations of information systems phenomena (Myers, 1997). Strauss and Corbin (1997) proposed the coding stages of open coding, axial coding, and selective coding to conceptualize an existing IS phenomenon. This method enabled the derivation of additional dimensions and characteristics and supported the adaption of taxonomy T_1. First, we could identify the dimension *key capability* by performing all coding stages. This describes the capabilities that are most relevant to achieve the respective value propositions and PPMs. Furthermore, an even more specific classification scheme for the application area could be defined. We renamed the dimension *value chain activity* to *business process type* and arranged the newly introduced characteristics along with the primary value chain activities. This implies the insertion of subdimensions as second-level groupings. Further, the coding showed that the actual *value contribution* of the IIoT application can be determined. The adapted taxonomy T_2 included six dimensions, six subdimensions, and 33 characteristics. As we have added further dimensions and characteristics in this iteration, the procedure continued with taxonomy T_2.

Iteration 3. We have selected the conceptual-to-empirical approach for the third iteration, as we intended to include further expert knowledge in the taxonomy creation procedure. We performed expert surveys with six practitioners from market-leading companies and six researchers with experience in IIoT and BPM. All experts received taxonomy T_2 and were asked to adapt or extend it. This interviewing procedure followed the method of Delphi studies, which supports soliciting information about a specific topic by completing several surveys (Loo, 2002). After a four-round Delphi study, we added seven additional characteristics for the dimensions *business process type*, *key capability*, and *value proposition*. In addition, we created the dimension *process specification* and demoted the dimension *process repetitiveness* to a subdimension. Eventually, we added the binary subdimension *knowledge intensity*. As stated by Davenport (2015), Gronau et al. (2005), and others, the amount of knowledge required for the performance of processes highly influences the deployment of technology and its automation. We identified several IIoT applications that could be classified under the formulated dimensions and characteristics. The adapted taxonomy T_3 included six dimensions, seven subdimensions, and 40 characteristics. As we have added further dimensions and characteristics in this iteration, at least one ending condition is not met. The procedure continued with taxonomy T_3.

Iteration 4. For the fourth iteration, the empirical-to-conceptual approach has been selected, as it may lead to new insights considering the adoptions performed in iteration 3. To find a new sample of objects, we selected 12 applications from Linde plc, a market-leading industrial company, and analyzed them using the grounded theory. As a result, no additional dimensions or characteristics could be identified. We checked the objective ending conditions and concluded that at least one object was classified under each dimension and characteristic. Further, every dimension and characteristic is unique and not repeated, and no additional dimensions or characteristics have been added. Checking the subjective ending conditions, both authors individually assessed the taxonomy as concise, robust, comprehensive, extendible, and explanatory. The procedure ended with iteration 4 and the unmodified taxonomy T_3.

4.3 Evaluation

As the *ex-ante* evaluation of checking the objective and subjective conditions has been solely performed by the authors, an adequate *ex-post* evaluation is required. In light of the intended taxonomy purpose, we defined three evaluation criteria that needed to be met to achieve the evaluation goals. For each of the criteria, we selected an evaluation method and an evaluation measure, as summarized in table 1. To follow the stream of existing research, we selected the most frequently used methods and criteria of prior taxonomy evaluations, as analyzed by Kundisch et al. (2021).

Evaluation criteria	**Method**	**Measure**
Reliability	Illustrative scenario	Dimension-specific hit ratios
Robustness	Illustrative scenario	Object-specific hit ratios
Completeness	Expert survey	Questionnaire results

Table 1. Evaluation approach.

Since the taxonomy should be used by researchers and practitioners to classify different kinds of possible IIoT applications within several industry branches, it must be robust. Robustness describes the artifact's ability to handle varying, and possibly low levels of information (Prat et al., 2015). Further, as it should enable different kinds of people to achieve similar or identical results for classifying the same objects, it must be reliable. Reliability constitutes the proportion of joint judgment in which there is an agreement (Nahm et al., 2002). Finally, the taxonomy should contain all necessary dimensions and characteristics to classify all objects of the phenomenon under consideration, represented by the criterion completeness.

To assess the **robustness** and **reliability** of the taxonomy, we used a sample of 30 illustrative scenarios from the literature and 10 real-life IIoT applications from Linde plc, a global market-leading company. To identify a new subset of literature objects without re-using those from the development steps, we performed a SRL analogously as in subsection 4.2, but changed the eligibility criteria. We now also considered publications with less than 50 citations, published not earlier than 2014, and excluded the already analyzed ones. If a publication mentioned more than one use case, we highlighted the one that needed investigation. For the final selection, we considered applications that cover at best all of the taxonomy's dimensions, subdimensions and characteristics. For the 10 real-life applications, we considered IIoT applications that cover a wide range of different technologies, business processes, and value chain activities. An expert panel of two researchers with knowledge in IIoT technology classified the sample using taxonomy T_3. The researchers have profound expertise in the underlying research field and had six weeks to classify the sample of objects. To select appropriate experts, we investigated researchers who have published at least two articles in the AIS „Basket of Eight" journals on the fields of IIoT and BPM. Furthermore, we specifically searched for researchers who have been involved in the development of taxonomies for IoT or BPM-related topics. From the identified group of researchers, we selected those two who are currently researching IoT and IIoT and therefore have up-to-date knowledge. For analyzing purposes we used the concept of hit ratios, representing inter-judge agreements within the expert panel (Nahm et al., 2002). This approach has proven to be appropriate for similar taxonomy evaluations as it renders the consensus within multiple classification results of the same application (Püschel et al., 2016). Agreement among the experts is counted as 1 and disagreement as 0 for all dimensions. Partially agreements of non-exclusive characteristics are coded on a scale from 0 to 1. To measure the robustness of the taxonomy, we compared the object-specific hit ratios of all IIoT applications from the literature with those from the real-life applications. As the literature applications only contain low to medium levels of information and the real-life applications have been discussed with the expert panel in detail, this comparison appropriately evaluates the robustness according to our definition. Eventually, the reliability is measured by assessing the dimension-based hit ratios (Moore and Benbasat, 1991) for measuring agreement among experts. Analyzing the results of the classifications, we also examined the exclusivity of characteristics and their scale. Table 2 shows the results of the classifications' dimension-specific results, whereas table 4 in the appendix includes all classified objects and hit ratios.

	Dimension Properties		
Dimensions	**Scale**	**Exclusivity**	**Hit Ratio**
Key Capability	Nominal	Non-exclusive	75%
Value Proposition	Ordinal	Non-exclusive	83%
Business Process Type	Nominal	Non-exclusive	85%
Process Specification	Nominal	Mutually exclusive	91%
Process Performance Measure	Nominal	Non-exclusive	81%
Process Perspective	Nominal	Non-exclusive	77%

Table 2. Dimension properties and dimension-specific evaluation results.

While all dimensions are nominally scaled, *value proposition* comprises characteristics with a specific type of order. Analyzing the classification results, we also conclude that most of the dimensions are non-exclusive, while only the characteristics of *process specification* are mutually exclusive. As already shown by Püschel et al. (2016), mutual exclusiveness within IoT-related taxonomies is hard to achieve due to the complexity and extent of applications. Yet, this does not pose a problem for its utility. The results for the dimension-specific hit ratios range between 75% and 91%, revealing an adequate consensus along with all experts. This showed us, that taxonomy T_3 complies with the criterion of reliability. However, while for the dimensions *business process type* and *process specification*, with ratios of 85% and 91%, high conformity have been reached, especially the dimensions *key capability* and *process perspective*, with ratios of 75% and 77%, seem to be not unambiguous. Analyzing the object-specific hit ratios, we achieved an overall hit ratio of 81% for literature-based applications and 85% for real-life applications. This small difference shows, that reasonable classification is possible in each case. Therefore, we conclude, that the taxonomy is also robust and can handle low levels of information in a manner that comes close to applications with higher levels of information.

To assess the taxonomy's **completeness**, we performed an expert survey. The expert panel consisted of 16 practitioners from five industrial companies that have working experience from four to 22 years. The industrial companies ranging from medium-sized to large multi-national corporations located in Germany, Sweden, the Netherlands, and the USA. At first, the expert panel had received the taxonomy including a comprehensive introduction and explanation of all dimensions and characteristics. Then, each expert classified a set of five to eight IIoT applications of their company using the given taxonomy.

Finally, after three weeks, the experts received a questionnaire where they needed to indicate if *i)* the taxonomy included all relevant dimensions and characteristics to classify the objects, *ii)* the definition of the taxonomy characteristics allowed a direct mapping with object characteristics, and *iii)* the dimensions and characteristics were detailed enough to allow differentiation between similar objects.

Statement	**Strongly agree**	**Agree**	**Neither agree nor disagree**	**Disagree**	**Strongly disagree**
The taxonomy includes all relevant dimensions and characteristics to classify the objects.	88%	12%	0%	0%	0%
The dimensions and characteristics are detailed enough to allow differentiation between similar objects.	81%	13%	6%	0%	0%
The definition of the taxonomy's characteristics allows direct mapping of all object characteristics.	75%	17%	8%	0%	0%

Table 3. Survey results.

Finally, we aggregated and assessed the expert survey results to evaluate the taxonomy's completeness. All experts agreed or strongly agreed with the statement, that the taxonomy included all relevant dimensions and characteristics to classify the objects. Further, 94% of the experts confirmed that the dimensions and characteristics are detailed enough to allow differentiation between similar objects, while 92% confirmed that the definition of the taxonomy's characteristics allowed a reasonable mapping with object characteristics. These results showed us, that the current taxonomy draft is complete.

Since the evaluation criteria have been met, we conclude that the current taxonomy draft T_3 reached the formulated evaluation goals. The hit ratios and the survey results proved that the taxonomy enabled the researchers and practitioners to *i)* describe, *ii)* classify, and *iii)* analyze the phenomenon of IIoT-based BPI applications. The objects' characteristics could be mapped with the taxonomy's dimensions and characteristics, while also a differentiation between similar objects was possible.

5 A Taxonomy of IIoT-based BPI Applications

To effectively communicate and illustrate the taxonomy, we have chosen the hierarchical tree technique as it has been adopted by a multitude of prior taxonomy designers. Also, it allows a clearer illustration and distinction of the taxonomy's elements compared with mathematical notations or tables. Figure 2 shows the final taxonomy of IIoT-based BPI applications. Consisting of six dimensions, seven subdimensions, and 40 characteristics, its size is in line with the recommendations of existing research without being too oversized or too marginal for complex classifications (Nickerson et al., 2013).

The IIoT comprises novel and disruptive capabilities that distinguish it from other technologies (Atzori et al., 2010). To enable beneficial BPIs, these capabilities must be used profitably and systematically. While the combination of these capabilities is often relevant for IIoT-based BPI, in most cases individual key capabilities can be identified that are exploited in particular. Thus, it is necessary to identify these key capabilities and focus on them while developing the application. Adding the dimension *key capability*, we state six characteristics that paraphrase the capabilities of IIoT. *Universal scalability* is the ability of the IIoT to adapt to changes in the environment and therefore enable the extension or adaption of existing information systems within processes (Gupta et al., 2017). Further, a *comprehensive perception* of the environment through sensors enables manifold monitoring and tracking applications (Tao et al., 2014). As IIoT applications often have the resources for edge computing directly on the shop floor, this *embedded intelligence* bridges the gap between the physical and digital worlds (Dai et al., 2019). Due to the different layers of an IIoT system, it is highly *configurable*, making the whole IIoT application flexible and customizable based on concrete business requirements. Another capability that originates from the layer architecture is the *interoperability* of the IIoT between systems and interfaces, which utilize different communication standards (Desai et al., 2015). Finally, as the IIoT is based on the connection of things via the internet, it can enable *connectivity* for any entity.

By exploiting the capabilities of the IIoT, potential *value propositions* can be defined which are the main drivers for the adoption, acceptance, and use of IIoT applications. *Situational awareness* describes the localization and condition assessment of objects at any time, e.g. by using RFID (Tai Angus Lai et al., 2018). One step further, IIoT systems can also be a tool for *decision-making support*. Here, extensive statistical models and big data analytics can reveal patterns that can simplify complex decisions making. *Information exchange* in IIoT can take place between things, things, and people, and between people. This enables the connection of different systems to perform complex tasks. Thus, IoT systems can actively control the course of processes and enable collaboration between actors (Schönig et al., 2018). Moreover, *autonomous systems* can analyze unpredictable situations and make automated decisions. Therefore, these IIoT systems can function independently of environmental conditions and human input.

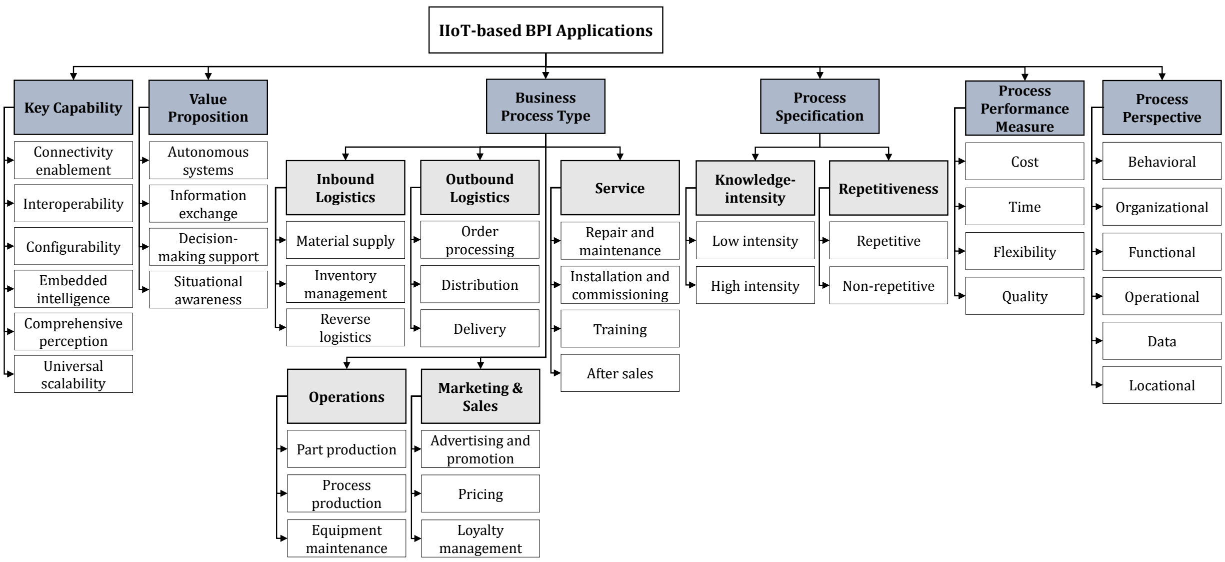

Figure 2. Taxonomy of IIoT-based BPI applications.

The nature of the IIoT application largely depends on the area of application and therefore the *business process type* in which it is embedded. The most common and widely used methodology to distinguish the activities of a company is the concept of value chains by Porter (1985). This helps to classify the IIoT applications based on the primary value chain activities, mapped as sub-dimensions. *Inbound logistics* comprises processes associated with *supplying raw materials*, *managing the inventories*, as well as *reverse logistics* of final products. Downstream, *operations* processes are responsible for transforming the raw materials into final products via *product* or *process production* and *maintaining* the used equipment. Subsequent, *outbound logistics* comprises the *processing of orders*, their *distribution*, and *delivery* to customers. Activities that provide the means to purchase the product are categorized as *marketing and sales*, including *advertising and promotion*, *pricing*, and *loyalty management*. Finally, *service* processes are associated with providing service to enhance or maintain the product's value (Barnes, 2000). This can be categorized as *repair and maintenance, installation and commissioning*, *training*, and *after sales*. For each of the stated subdimensions and characteristics, or process types, the implemented IIoT applications differ significantly. This is the case due to different objectives, process actors, and interfaces to internal or external information systems and stakeholders.

In addition to the exploited IoT capabilities and the business process type, to appropriately classify an IIoT-based BPI application, the underlying *process specification* needs to be analyzed as it has a major influence on the actual IIoT application and the achievable BPI. Especially the *knowledge-intensity* and *repetitiveness* of processes increase the requirements for IIoT applications and may limit the actual BPI, as they represent the degree of variety and complexity. Processes with a high knowledge-intensity often require human judgment (vom Brock et al., 2016) and can only be partially automated due to unpredictable decisions or tasks (Gronau et al., 2005). In addition, traditional methods for process measurement and BPI seem to be inappropriate due to their unstructured and often collaborative nature (Benešová et al., 2019). This also applies to non-repetitive processes as they require more detailed planning and hamper the use of novel technologies (Thiemich and Puhlmann, 2013).

Apart from classifying an IIoT application in terms of IIoT-related or process-related characteristics, it is necessary to determine the expression of actual BPIs. One possibility of quantifying this is to define various key performance indicators (KPIs), in the context of BPM also called *PPMs*. PPMs can take different forms depending on the type of process and the desired output, but most of the literature defines PPM in terms of *time*, *cost*, *quality*, and *flexibility (*Dumas et al., 2018). The characteristic *time* may have different forms, e.g., the cycle time, processing time, or waiting time. The *costs* associated with processes consist of various components, such as wage costs, IT costs, or service costs. A definition of the PPM *quality* is more complex and could constitute, e.g., the performance of workflows or processes without deviations in an anticipated way. Lastly, the characteristic *flexibility*, i.e. the responsiveness of the process to changes in the environmental conditions, must also be made measurable.

Finally, an IoT application, and particularly the resulting BPI, can influence one or multiple specific perspectives of a business process. Therefore, the dimension *process perspective* outlines, which constituents of the process are influenced most by the BPI. In that regard Jablonski and Bussler (1996) and Schönig et al. (2014) have formulated six process perspectives. The *behavioral perspective* mainly comprises elements of the right process workflow or sequence, legal regulations such as reporting obligations, and internal requirements. The *organizational perspective* focuses on the personnel that is involved in the process execution and monitoring. Its main components are responsible process owners, admins, and process users. In addition, the underlying system is part of this perspective and represents for example the IT environment. The *functional perspective* includes the concrete process steps, activities, and events. Most of the processes, especially in the manufacturing industry, comprise several facilities, machines, tools, software applications, or items that can be described as the *operational* perspective. The *data perspective* involves all data and documents that are necessary for process execution. Finally, the *locational* perspective is also relevant, as assigning tasks to participants and the progression of a process may then depend on specific locations. With complex processes including human workers and machines, the locational attributes are highly relevant and can be influenced and exploited by IIoT systems.

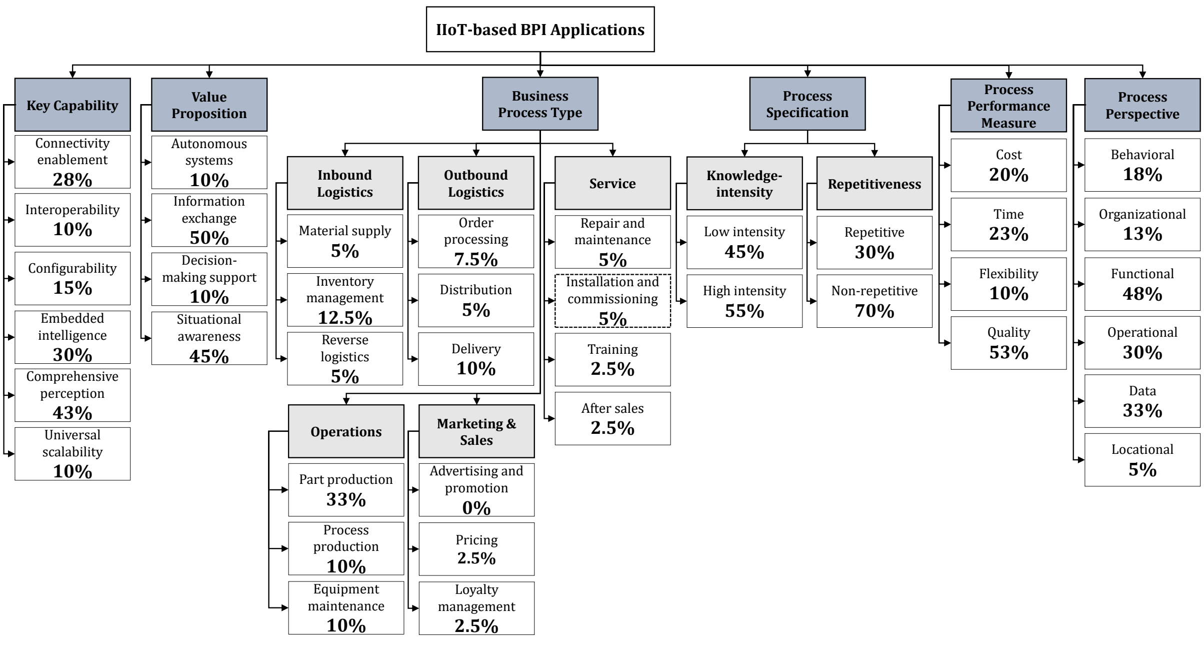

Figure 3. Classification results.

To provide even deeper insights into the characteristics of IIoT-based BPI applications, we calculated the ratios of all classifications performed in subsection 4.3. Figure 3 illustrates the characteristics' absolute ratios for the 40 classified literature and real-life applications. The sum of all characteristics might exceed 100% for non-exclusive dimensions. The results for key capability show that most of the applications exploit the capabilities comprehensive perception and embedded intelligence. This highlights the importance of sensors, actuators, and distributed computing paradigms associated with the IoT, e.g., edge computing. Analyzing the value proposition ratios, we conclude that basic awareness of the environment and process parameters as well as exchanging information is most relevant. With only 10%, *autonomous systems* are not represented often, although the automation of whole processes has the most significant leverage for BPI. This reveals the need for further research to enable this value proposition. The distribution of applications shows, that a focus lies on operations and logistics processes with a ratio of 53%. We could identify a lack of use cases in marketing and sales which, however, could be the source for major BPIs. For the mutually-exclusive subdimensions of *process specification*, no clear trend could be derived. More than half (53%) of all applications focused on improving the process quality. This is reasonable, as most simple monitoring and tracking use cases do not have a direct link to the cost, time, or flexibility measures. These applications increase the overview and transparency, and thus the quality of the processes. Finally, almost half of the applications (48%) influenced the functional *process perspective* representing the actual process tasks and activities.

6 Conclusion and Future Research

Though its importance and relevance, a systematic classification of IIoT applications aiming at BPI has not been addressed so far. Yet, classifications are highly relevant as they provide a structure and an organization to the knowledge of an existing field of research (Glass and Vessey, 1995). We, therefore, developed a taxonomy of IIoT-based BPI applications following the development procedure of Nickerson (2013) and its extension by Kundisch et al. (2021). Combining inductive and deductive methods, the resulting taxonomy consists of six dimensions, seven subdimensions, and 40 characteristics. From a research perspective, it adds to the descriptive knowledge of the IIoT and provides a starting point for further research. From a managerial or practical point, the taxonomy supports a classification of all kinds of IIoT applications within business processes. The resulting information can be used to compare existing applications with those of competitors or to ensure that dimensions relevant to IIoT applications can be considered entirely for future projects. From the perspective of an IIoT solutions provider, the taxonomy helps identify relevant components of IIoT applications and potentials for developing novel technologies. Although being developed according to DSR principles, including an extensive evaluation, the final taxonomy is not without limitations. First, the selection of an approach for each development iteration, the ending conditions, and the included literature during the SLR highly influenced the taxonomy creation. Different approaches and literature may have led to different taxonomies. However, this is not a fundamental issue, as DSR allows varying artifacts for varying preconditions (Hevner et al., 2004). Another limitation is the non-exclusiveness of some characteristics and, therefore, minor redundancies. Though, this does not contradict or violate the general utility and applicability of the taxonomy. For each specific combination of characteristics, an own characteristic might be introduced, resulting in a mutually exclusive but inflated set of characteristics (Püschel et al. 2016). Moreover, the taxonomy's dimensions are not perfectly orthogonal, i.e., the characteristics of each dimension cannot be arbitrarily combined with characteristics of any other dimension (Püschel et al. 2016). This implies, that some combinations of characteristics are rather unlikely to happen. That is especially the case, as particular value propositions require the exploitation of specific key capabilities. In section 5, we stated the classification results for a sample of 40 IIoT applications. As this sample has been selected mainly for evaluation purposes, it might be too small to represent the broad range of applications. To ensure representativity, a larger sample of IIoT applications could be classified. Future research should re-evaluate and apply the taxonomy for further validation.

Appendix

Literature Object (Reference)	Key Capability	Value Proposition	Business Process Type	Process Specification	PPM	Process Perspective	Hit Ratio (Object)
Ayvaz and Alpay (2021)	0.67	0.00	1.00	1.00	0.67	0.50	**0.67**
Bag and Wood (2019)	0.50	1.00	1.00	1.00	0.50	1	**0.83**
Civerchia et al. (2017)	0.00	1.00	1.00	1.00	1.00	0.75	**0.79**
Compare et al. (2020)	0.75	1.00	1.00	1.00	1.00	0.75	**0.92**
Dhungana et al. (2021)	0.86	1.00	1.00	1.00	0.67	0.40	**0.82**
Garrido-Hidalgo et al. (2019)	1.00	0.00	1.00	0.50	1.00	0.75	**0.71**
Gnoni et al. (2020)	0.76	1.00	1.00	0.50	0.67	1.00	**0.82**
Guerra-Zubiaga et al. (2021)	1.00	1.00	1.00	1.00	0.75	1.00	**0.96**
Guo (2021)	1.00	1.00	1.00	1.00	0.50	1.00	**0.92**
Hofmann and Rüsch (2017)	0.67	1.00	1.00	1.00	1.00	0.50	**0.86**
Jose (2018)	0.75	1.00	1.00	1.00	1.00	1.00	**0.96**
Kessler et al. (2019)	1.00	1.00	1.00	1.00	1.00	0.67	**0.95**
Kumar et al. (2018)	0.75	0.00	1.00	1.00	1.00	0.50	**0.71**
Lee et al. (2017)	0.50	1.00	1.00	1.00	0.75	1.00	**0.88**
Leng et al. (2021)	1.00	1.00	0.00	0.50	1.00	0.67	**0.70**
Liu et al. (2018)	0.67	0.00	1.00	1.00	0.75	0.75	**0.70**
Liu et al. (2019)	0.50	1.00	0.00	1.00	0.00	1.00	**0.58**
Mohsin and Yellampalli (2017)	0.00	1.00	1.00	1.00	1.00	0.40	**0.73**
Moradi (2021)	1.00	1.00	0.00	1.00	1.00	0.33	**0.72**
Nyato et al. (2016)	0.67	1.00	1.00	1.00	1.00	1.00	**0.95**
Ploder et al. (2021)	0.80	0.00	1.00	1.00	0.33	1.00	**0.69**
Rasmussen and Beliatis (2019)	0.86	1.00	1.00	0.50	0.67	0.50	**0.75**
Reljić et al. (2021)	1.00	1.00	1.00	1.00	1.00	1.00	**1.00**
Sasiain et al. (2020)	1.00	1.00	1.00	0.50	0.50	1.00	**0.83**
Schneider et al. (2019)	0.75	0.00	1.00	1.00	1.00	0.00	**0.63**
Schönig et al. (2018)	0.80	1.00	0.00	1.00	0.50	1.00	**0.72**
Taylor et al. (2018)	0.75	1.00	1.00	1.00	1.00	1.00	**0.96**
Ursu et al. (2020)	0.80	1.00	1.00	1.00	0.50	1.00	**0.88**
Yerra and Pilla (2017)	0.75	1.00	1.00	1.00	1.00	0.00	**0.79**
Zhu (2021)	0.86	1.00	0.00	1.00	1.00	1.00	**0.81**
Real-life Object from the Linde plc							
Authorization Check	0.75	1.00	1.00	1.00	0.75	1.00	**0.92**
Deviation Detection	1.00	1.00	0.00	1.00	1.00	1.00	**0.83**
Location-based Safety Check	0.67	1.00	1.00	1.00	0.33	0.50	**0.75**
Manufacturing Process Guidance	0.67	1.00	1.00	0.50	1.00	1.00	**0.86**
Predictive Maintenance	0.50	1.00	1.00	1.00	1.00	0.50	**0.83**
Pressure Monitoring	1.00	1.00	1.00	0.50	0.75	0.75	**0.83**
Process Data Visualization	0.67	0.00	1.00	1.00	1.00	1.00	**0.78**
Remote Maintenance Support	0.67	1.00	1.00	1.00	1.00	1.00	**0.96**
Visual Customer Guidance	0.75	1.00	1.00	1.00	0.75	0.50	**0.83**
Warehouse Tracking	0.67	1.00	1.00	1.00	1.00	1.00	**0.95**
Hit Ratio (Dimension)	**0.75**	**0.83**	**0.85**	**0.91**	**0.81**	**0.77**	

Table 4. Hit ratios of classification results.

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