COPPE
UFRJ
Instituto Alberto Luiz Coimbra de
Pós-Graduação e Pesquisa de Engenharia

A KNOWLEDGE-BASED APPROACH TO SUPPORT INTERNET OF EVERYTHING (IoE) LIFESTYLE

Viviane Cunha Farias da Costa

Tese de Doutorado apresentada ao Programa de Pós-graduação em Engenharia de Sistemas e Computação, COPPE, da Universidade Federal do Rio de Janeiro, como parte dos requisitos necessários à obtenção do título de Doutor em Engenharia de Sistemas e Computação.

Orientador: Jano Moreira de Souza

Rio de Janeiro
Março de 2022

A KNOWLEDGE-BASED APPROACH TO SUPPORT INTERNET OF EVERYTHING (IoE) LIFESTYLE

Viviane Cunha Farias da Costa

TESE SUBMETIDA AO CORPO DOCENTE DO INSTITUTO ALBERTO LUIZ COIMBRA DE PÓS-GRADUAÇÃO E PESQUISA DE ENGENHARIA DA UNIVERSIDADE FEDERAL DO RIO DE JANEIRO COMO PARTE DOS REQUISITOS NECESSÁRIOS PARA A OBTENÇÃO DO GRAU DE DOUTOR EM CIÊNCIAS EM ENGENHARIA DE SISTEMAS E COMPUTAÇÃO.

Orientador: Jano Moreira de Souza

Aprovada por: Prof. Jano Moreira de Souza
Prof. Weiming Shen
Prof. Geraldo Bonorino Xexéo
Prof. Luiz Felipe Silva Oliveira
Prof. Daniel Serrão Schneider

RIO DE JANEIRO, RJ - BRASIL
MARÇO DE 2022

Costa, Viviane Cunha Farias da

A Knowledge-based approach to support Internet of Everything (IoE) lifestyle/ Viviane Cunha Farias da Costa. – Rio de Janeiro: UFRJ/COPPE, 2022.

XVII, 201 p.: il.; 29,7 cm.

Orientador: Jano Moreira de Souza

Tese (doutorado) – UFRJ/ COPPE/ Programa de Engenharia de Sistemas e Computação, 2022.

Referências Bibliográficas: p. 167-200.

1. Internet das Coisas. 2. Sensores Inteligentes. 3. Gestão do Conhecimento. I. Souza, Jano Moreira. II. Universidade Federal do Rio de Janeiro, COPPE, Programa de Engenharia de Sistemas e Computação. III. Título.

Aos meus filhos Carlos Eduardo, Pedro Henrique e João Guilherme

Agradecimentos

Primeiramente: À Deus, pelo dom da vida, por tudo.

Aos meus filhos, Carlos Eduardo, Pedro Henrique e João Guilherme. Vocês são a razão, inspiração e orgulho da minha vida! Amo vocês!

Aos meus pais, Antonio e Tereza que sempre me incentivaram em todos os momentos e me ensinaram o valor da educação. Devo tudo a vocês.

Ao meu marido Eduardo, pelo apoio e compreensão.

Aos meus irmãos Ary e Bruno pelo incentivo e torcida.

Ao meu orientador Professor Jano Moreira de Souza, pelos ensinamentos, pela confiança que sempre depositou em mim e pela orientação segura que me permitiu chegar até aqui após longos anos.

Aos professores Weiming Shen, Geraldo Bonorino Xexéo, Luiz Felipe Silva Oliveira e Daniel Serrão Schneider, por terem gentilmente aceitado participar da banca de defesa da tese.

Agradeço também aos amigos e à equipe da UFRJ, da COPPE e do PESC, pelo suporte durante todos esses anos.

À Marinha do Brasil, por confiar-me a nobre missão de realizar o doutorado.

Resumo da Tese apresentada à COPPE/UFRJ como parte dos requisitos necessários para a obtenção do grau de Doutor em Ciências (D.Sc.)

A KNOWLEDGE-BASED APPROACH TO SUPPORT INTERNET OF EVERYTHING (IoE) LIFESTYLE

Viviane Cunha Farias da Costa

Março/2022

Orientador: Jano Moreira de Souza

Programa: Engenharia de Sistemas e Computação

Internet de Todas as Coisas ou "*Internet of Everything"* (IoE) é o paradigma de serviços inteligentes que suporta um mundo onipresente e ultra conectado, levando a mudanças sociais relevantes. Nesse contexto, é essencial a identificação e o claro entendimento sobre processos de conhecimento entre máquinas e humanos e a identificação de facilitadores de IoE (pessoas, processos, dados e coisas) para lidar com a era da digitalização. Esta tese apresenta uma Taxonomia Baseada em Conhecimento para apoiar o entendimento sobre o paradigma de IoE e um Modelo Integrado de Gestão do Conhecimento desenvolvido para dar suporte à evolução de serviços inteligentes em IoE. Foram definidos requisitos de inteligência para avaliar o nível de conhecimento de sensores e atuadores em aplicações de IoE. Além disso, um ambiente colaborativo, o IoE Database (IoEDB) suporta a evolução da taxonomia proposta, a curadoria dos facilitadores de IoE ("IoE *enablers"*), além de apoiar a gestão do conhecimento em aplicações de IoE.

Abstract of Thesis presented to COPPE/UFRJ as a partial fulfillment of the requirements for the degree of Doctor of Science (D.Sc.)

A KNOWLEDGE-BASED APPROACH TO SUPPORT INTERNET OF EVERYTHING (IoE) LIFESTYLE

Viviane Cunha Farias da Costa

March/2022

Advisor: Jano Moreira de Souza

Department: Computer and Systems Engineering

The Internet of Everything (IoE) is the paradigm of intelligent services that supports a ubiquitous and always connected smart world, leading to relevant societal changes. In this context, it is essential to have a comprehensive awareness of knowledge processes in human-to-machine interactions and IoE enablers (people, processes, data, and things) to ensure readiness for the digitalization era. This thesis presents the IoE Knowledge-based Taxonomy to support awareness of the IoE context. An Integrated IoE Knowledge Management Model is developed to support the evolution of smart services in IoE. Smartness requirements were defined to rank knowledge of sensors and actuators in IoE applications. Additionally, a collaborative environment, IoE Database (IoEDB) supports the evolution of the 'live' IoE proposed taxonomy, the curation of IoE enablers, and knowledge management of IoE applications.

Contents

List of Figures

List of Tables

List of Abbreviations

ASIoT	Application-Specific Internet of Things
AI	Artificial Intelligence
CPU	Central Processing Unit
CIoT	Cognitive Internet of Things
CS	Cognitive Sensing
CMS	Content management system
CPS	Cyber-Physical Systems
DC	Data collection
DSR	Design Science Research
EIoT	Education Internet of Things
E-IoT	Enterprise Internet of Things
FSG	Fog Smart Gateway
FIoT	Future Internet of Things
GIoT	Green Internet of Things
GSD	Green Smart Service
H2H	Human to Human
H2M	Human to Machine
IIoT	Industrial Internet of Things
IaaS	Infrastructure as a Service
IED	Intelligent eletronic devices
IoAT	Internet of Animal Things
IoA	Internet of Anything
IoBT	Internet of Battle Things
IoB	Internet of Bins
IoD	Internet of Drones
IoE	Internet of Everything
IoEDB	Internet of Everything Database
IoHT	Internet of Health Things
IoMT	Internet of Medical Things
IoMT	Internet of Multimedia Things
IoMusT	Internet of Musical Things

IoNT	Internet of Nano Things
IoOT	Internet of Old Things
IoP	Internet of People
IoP	Internet of Planets
IoRT	Internet of Robotic Things
IoS	Internet of Ships
IoST	Internet of Softwarized Things
IoTT	Internet of Tangible Things
IoT	Internet of Things
IoTK	Internet of Thinking
IoUGT	Internet of Underground Things
IoUT	Internet of Underwater Things
IoV	Internet of Vehicles
IoWT	Internet of Waste Things
IoX	Internet of X
KA	Knowledge Assets
KM	Knowledge Management
LEO	Low Earth Orbit
LPWAN	Low Power Wide Area Network
ML	Machine Learning
M2M	Machine to Machine
MCC	Mobile Cloud Computing
MCS	Mobile Crowd Sensing
MEC	Mobile Edge Computing
MCDM	Multi Criteria Decision Making
OS	Operation System
PRP	Parallel redundance protocol
P2M	People to Machine
QoS	Quality of Service
RT	Real-time
RTA	Recognition-transduction-acquisition
SSN	Semantic Sensor Network
SSNT	Semantic Social Network of Things

SWoT	Semantic Web of Things
SEM	Smart Environment Monitoring
SGB	Smart Garbage Bin
SG	Smart Grid
SO	Smart objects
SS-Net	Smart Sensor Network
STI	Smart Transducer Integrator
SCIoT	Social Colaborative Internet of Things
SIoT	Social Internet of Things
SN	Social Network
SDSR	Soft Desing Science Research
SDIoT-Fog	Software Defined Internet of Things - Fog
SDN	Software Defined Network
VANET	Vehicular Adhoc Network
VM	Virtual Machines
WoT	Web of Things
WSN	Wireless Sensor Network

1. Introduction

This chapter describes what motivated this investigation, defining the research goals and questions. Besides, it presents an overview of the research approach, highlighting the main results. Finally, it presents the outline of this document.

1.1 Context and Motivation

Internet of Things (IoT) is defined as a network of 'things' connected around the world, including everyday objects, devices, sensors, actuators, and any other devices connected over the Internet to other objects: in the physical or virtual world to achieve a specific goal (SCHATTEN; ŠEVA; TOMIČIĆ, 2016) (WHITMORE; AGARWAL; XU, 2015) (CHARMONMAN; MONGKHONVANIT, 2015) (RISTESKA STOJKOSKA; TRIVODALIEV, 2017).

The denomination of IoT presents the two terms "Internet" and "Things", to represent that different applications can share freely and on a global scale the sources of information (ATZORI; IERA; MORABITO, 2017). The first reflects a vision of communication, properly organized in the form of a generic network (i.e. the Internet, in the acronym IoT), the second tends to shift the focus to physical objects, the "things" to be connected (ARDITO; D'ADDA; MESSENI PETRUZZELLI, 2017)(ETZION; FOURNIER; ARCUSHIN, 2014).

Internet of Everything (IoE) is a much broader concept (YANG; DI MARTINO; ZHANG, 2017), defined as:

"*a network of networks that brings together people, process, data, and things to make network connections more relevant and valuable than ever before"* (EVANS, 2012).

My research interest in IoE expands the concept to people, business processes, and generated interactions, as there is great potential to be explored about extracting value from the interactions between sensors and actuators (human and non-humans) in this complex computational environment (FARAHZADI *et al.*, 2017) (IRSHAD, 2016), where the Internet, becomes intrinsic to people's lives and ubiquitous through networked devices (KHODADADI; DASTJERDI; BUYYA, 2016)(IRSHAD, 2016), surrounding the beginning of a new paradigm defined as “IoE lifestyle”.

Research on knowledge management has focused on understanding the complex relationships between data, information, and knowledge creation, and how they are impacted and benefited by the sources (or spaces) of data and information and the contexts in which they are analyzed and shared (PHILIP, 2018).

Several paradigms based on the Internet and connecting multiple entities are under the IoE umbrella, such as the Internet of Things (IoT), the Internet of People (IoP), and Industrial Internet (II). For this thesis, I will consider all of them as a subdomain of IoE, as will be explained in Section 2.1.1.

Following my research motivations, this thesis will delve deeper into the knowledge management approach for intelligent service evolution in IoE applications.

The successful adoption of a particular technology depends on the comprehension of its use and features (AL-EMRAN *et al.*, 2018). There is still a fragmented framework in IoE research: (1) A lack of consensus and new demands are unique to the IoE context (e.g., empowering people and providing intelligence services and insights through the collaboration of IoE enablers [sensors and actuators]); and (2) A lack of consideration for integration of IoE connections perspectives — the perspective of knowledge and type of data sources, the perspective of the observation (the context), and the perspective of infrastructure capabilities.

In this thesis, the main contribution is to investigate research challenges in the IoE paradigm and a way forward in the classification of IoE knowledge enablers (sensors and actuators) to support the identification of critical knowledge flows that lead to actionable intelligence in IoE applications. A systematic literature review of existing IoE and IoT taxonomies was conducted, and from this, a knowledge-based IoE taxonomy was developed which provides a consistent picture of IoE systems and their constituents (i.e., IoE sensors and actuators characterized in knowledge processes, observations, and network characteristics). Additionally, a systematic literature review of smart sensors in IoE and IoT was conducted, and from this, 18 smartness requirements were defined to evaluate and rank knowledge in IoE smart sensors and actuators.

Additionally, the focus is leveraging awareness of intelligence sources in IoE application, considering IoE enablers and observation capabilities (WHITMORE; AGARWAL; XU, 2015). This thesis proposes integrating service science and knowledge management research to support the e-governance of IoE applications for intelligence service evolution. For this, to support awareness of information sources, the IoE Knowledge-based taxonomy was developed: 18 dimensions distributed in 4 categories are organized to support awareness of the IoE context. From a practical standpoint, this work demonstrated the IoE Knowledge-based taxonomy's practical applicability and its evolution in a web-based knowledge management system: the IoE Database (IoEDB). Moreover, an IoE Integrated Knowledge Management (KM) Model is proposed to guide service evolution and knowledge management in IoE applications. This approach leverages awareness of intelligence sources in IoE applications, considering IoE enablers and observation capabilities, through a KM strategy.

1.2 Problem Definition and Research Question

Value creation from IoE solutions is complex since it embodies human and non-human sensors and actuators, in a cyber-physical environment, networked in heterogeneous platforms with diverse systems characteristics. Moreover, tacit knowledge from humans, explicit knowledge in data sources, and implicit knowledge in AI (artificial intelligence) and data analysis are intertwined, in distinct interactions for its realization.

Unlike traditional systems, IoE applications enable:

- Smart sensors and actuators (things and people) as intelligent nodes in IoE relevant connections.
- Observation facilities and monitorability in wide deployment of sensing infrastructure for smart applications.
- Data analytics and artificial intelligence (AI) transparency in support of decision-making processes.

- Processes and intelligent services evolution through a value co-creation process.

My investigation in this research seeks to be more comprehensive in the sense of knowledge management in IoE applications and identifying knowledge flows between people (as human sensors) and things (cyber-physical sensors) in IoE applications.

My motivation to investigate and contribute to the understanding and evolution of the IoE paradigm is therefore supported by following defined problems:

1) The transformation of the Internet from a communication network to a control network embedded directly into the physical world and the advent of the digital society demands preparedness to obtain benefits from the IoE lifestyle. (General)

2) IoE and KM can leverage each other for creating intelligent ecosystems by combining emergent IoE enablers (sensors and actuators) and KM processes. But it demands awareness of IoE context and a specific IoE KM Model. (Specific)

Benefiting from the IoE lifestyle demands more than a technological perspective since IoE solutions usually cover collaboration of people and things in machine-to-people (M2P), machine-to-machine (M2M), and people-to-people (P2P) connections for knowledge sharing, a pervasive observation context, and ubiquitous communication alongside the design of a complete solution. Thus, this thesis is conducted in a multidisciplinary way.

This evolution is now considered an evolution centered on many actors ("everything"), that is, on the creation of networks of people, data, things – contributing for intelligent services in the IoE paradigm.

With the expansion to the IoE paradigm, people are sensors and actuators, with intelligent capabilities (competencies). However, there is still a need to evolve research to address the collaboration and the knowledge flows specificities in the IoE scenario.

The thesis seeks to answer the following research question:

How a knowledge-based strategy to address knowledge flows in M2M, H2H, and M2H interactions assists in enhanced intelligent services in IoE applications?

1.3 Research Goal

The main objective of this work is to propose an approach for knowledge management in the IoE context with focus on knowledge flows between human and non-human intelligent sensors, collaborating for knowledge creation and collective intelligence.

Regarding IoE comprehensive view, in addition to presenting existing challenges, with this work, the proposed artifacts should be:

• Generic enough, at a higher level of abstraction, to support their collaborative evolution, regarding dynamics and characteristics of the IoE paradigm.

• Flexible enough to be extended and evolved so that it continues to represent the IoE paradigm.

• Adaptable enough so that it can be instantiated more concretely in different applications applied in the IoE environment.

Thus, to address knowledge flows between M2M, H2H, and M2H interactions, the objective of this thesis can be broken down and better detailed in the following sub-objectives:

- Investigate a common ground and research gaps in IoE research and explore the relationship between IoE and Knowledge Management (KM).
- Create a taxonomy to classify and identify IoE enablers, to support IoE knowledge identification.
- Create an IoE Integrated Knowledge Management Model (regarding IoE, Service Science, and KM).
- Develop a web-based collaborative environment to support IoE Knowledge Management, the proposed IoE Database.
- Validate and evaluate the artifacts in distinct IoE domains (ranking knowledge in IoE crowdsourcing applications, ranking knowledge in smart sensors and validate the proposed taxonomy with 50 IoE applications to prove its quality attributes and identify research challenges.

- Validate the IoE Integrated Knowledge Management Model.

Therefore, this work aims at minimizing the complexity of the IoE paradigm and encouraging researchers in distinct fields, users, and society while maximizing its expressiveness and benefits for connected society and collective intelligence.

This thesis depicts IoE applications as a set of IoE enablers that support IoE experiences such as knowledge, sensors, observations, and technological capabilities. This approach supports the understanding and definition of fine-grained IoE characteristics.

To clarify the objective described above, this research will address the following research questions (RQ):

RQ1: How to apply knowledge management (KM) strategy in the context of IoE with a focus on collective intelligence and knowledge flows between M2M, H2H, and M2H interactions?

RQ2: How to promote service enhancement and evolution in the IoE context to deliver greater value to connected society?

RQ3: How to identify and evaluate (rank) knowledge sources in the IoE context?

These contributions were communicated in scientific forums from 2020 to 2022, through scientific publications, described below and summarized in Table 1.

Table 1. Research Questions

RQ	Title	Published in
RQ1 and RQ2	Internet of Everything (IoE) Taxonomies: A Survey and a Novel Knowledge-based Taxonomy	MDPI Sensors 2021
RQ1 and RQ3	Towards a taxonomy for ranking knowledge in Internet of Everything	CSCWD 2021
RQ1	A collaborative approach to support interoperability and awareness of the Internet of Everything (IoE) enablers	ICHMS 2021
RQ1 and RQ3	Relatório Técnico: Internet of Everything (IoE) Taxonomy	PESC Publications
RQ1 and RQ3	An approach for intelligence evaluation in smart sensors	CSCWD 2022 (accepted)

The thesis is based on the three premises below:

1. Collective intelligence is dynamically created by knowledge sharing within the IoE context.

2. The perceived value of IoE applications arises from the use of intelligent services.

3. Service design benefits from understanding enablers identification in the IoE environment.

1.4 Methodology

Design Science Research (DSR) is the problem-oriented research paradigm that operationalizes Design Science. Design Science aims at the guided use of technology through principles and guidelines too high-level to guide practice (ALTURKI; GABLE; BANDARA, 2011; BASKERVILLE; PRIES-HEJE; VENABLE, 2009) (PEFFERS *et al*., 2007). Although DSR artifacts approach research (theory) with practice, it does not seek the optimal solution, but the satisfactory solution for a specific problem related to human goals.

HEVNER *et al.* (HEVNER *et al.*, 2004), proposed a set of criteria to support the execution of DSR in the information systems research field. Figure 1 shows a set of following criteria to be adopted by researchers in search of a solution.

1. The specific problem is identified and outlined.

2. The problem is expressed as a set of specific requirements.

3. In the systems world, the specific requirements are abstracted and translated to a general problem.

4. A general solution is then developed based on a set of general requirements.

5. The general and specific requirements are compared (2 and 4).

6. A search is done for the specific components that will provide an effective instance of a solution to the general requirements.

7. An instance of the specific solution is built and deployed in the social system, thus changing the specific problem, allowing learning to be derived, and starting the cycle again.

This thesis applies the Soft Design Science Research (SDSR) methodology in the development of the proposed artifacts. The referred methodology involves concepts of Design Science Research (DSR) (DRESCH; LACERDA; ANTUNES, 2014) and the Soft Design Science Research (SDSR) methodology (BASKERVILLE; PRIES-HEJE; VENABLE, 2009) (a research approach to artifact design in the area of information systems design). The SDSR design process involves forming hypotheses, experimenting with artifacts (construction), and comparing the results (evaluation) in a projecting loop (construction ↔ evaluation) until the usefulness of the artifact is obtained and validated.

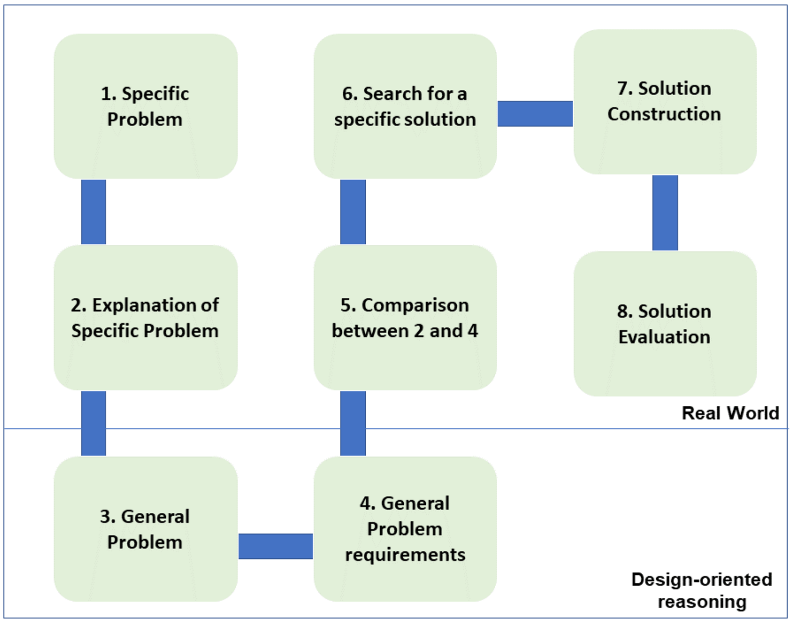


Figure 1. Design Science Research

The methodology was applied in each design phase of this research execution.

<u>1. Specific problem</u>

The first step of the SDSR methodology is the definition of the specific problem. It takes place in the real world. In the first step of the method, a specific problem is defined and outlined. To clarify the definition of the specific problem, the following specific-problem questions (SP) were developed and will be answered in the conclusion section of this thesis.

SP1: How IoE and KM can leverage each other for creating intelligent IoE ecosystems?

SP2: How to identify knowledge flows between sensors and actuators in P2P, P2M and M2M interactions?

SP3: How to support the evolution of smart services in IoE using a KM strategy?

2. Explanation of the Specific Problem in Specific Requirements (SR)

This step also occurs in the real world. In this step, the problem is detailed through a set of requirements. The following specific requirements (SR) have been defined to address the specific issue. This step allows the construction and execution of the artifact for evaluation.

SR1: Identify and characterize the sources of knowledge in IoE applications contemplating human-machine knowledge (Aiming to address problem SP2).

SR2: Create a model/mechanism/process for Knowledge Management in IoE applications (aiming to address the problem SP1 and SP3).

3. General Problem (GP)

This step takes place in the abstract world in which the requirements of the specific problem are systematically generalized into a general problem adopting technical and social dimensions. In this step, a specific problem will be transformed into a general problem. From this generalization, a class of problems is defined that will guide the research in the literature to be developed in Chapters 2 and 3.

General:

GP1: Investigate how KM in IoE can positively influence the creation of collective intelligence.

GP2: Understand how intelligent services and relevant connections in IoE may benefit from KM strategy.

4. General Problem Requirements (GR)

From the definition of a class of problems in the previous step, the fourth step seeks a class of solutions to a general problem. From the definition of a class of problems, this step seeks a class of solutions to the general problem. The requirements to meet general issues are:

GR1: Investigate the state of the art of research on Knowledge Management (KM) that includes the dynamics of IoE and the knowledge flow between people and machines.

GR2: Map knowledge management strategies that improve the quality of services in IoE applications.

5. Comparison between specific problem (SP) statements and general requirements (GR)

In the fifth step, the review of the requirements of the specific problem (SR) is done by comparing them (step 2) with the general requirements (step 4). In this step, the explanation of the specific problem is reviewed according to the general requirements.

6. Search for a specific solution

In the sixth step, the search for a specific solution is based on the general requirements mapped in the previous step. A set of actions is established based on these requirements.

Revisiting the general requirements defined above, the following actions will be developed:

Action 1: Development of an IoE taxonomy of sensors and actuators specific to the IoE context that supports identification and awareness regarding the knowledge flows. (Chapter 3)

Action 2: Development of the IoE Integrated KM Model (IoE IKM Model) which addresses the design of intelligent services in IoE applications. (Chapter 3)

Action 3: Development of a collaborative environment to support IoE KM strategy and the evolution of the proposed IoE taxonomy. (Chapter 3)

7. Construction of the solution

This step involves building and evaluating whether the problem has indeed been solved. In addition, the lessons learned during all stages must be made explicit. The construction of the artifacts is described in Chapter 3.

8. Artifact evaluation

This step involves evaluating the artifact. The evaluation step is described in Chapter 4. This step also involves whether the problem has been resolved or if it has been modified. Learning along the stages must be explained and a new cycle must be started if necessary.

1.5 Main Results

In addition to the main contribution, there are some other contributions present in this work:

1. Investigation of state of art about the IoE paradigm and trends in KM research.

2. Investigate how to identify opportunities for serendipity in digital environments (Internet-based paradigms) related to the proposed approach.

3. Survey of the state of the art of KM models disseminated in the literature and related to Internet paradigms and propose a specific IoE Integrated KM Model (IoE IKM Model) for the evolution of intelligent services in IoE.

4. The proposal of the IoE Knowledge-based Taxonomy and its validation in 50 applications in different domains.

5. A proposal of a collaborative environment (IoE Database) to evolve the taxonomy and support the KM strategy for the evolution of intelligent services in IoE.

Different contributions were achieved throughout this research and are presented in this thesis:

- Farias da Costa, V.C.; Oliveira, L.; de Souza, J. Internet of Everything (IoE) Taxonomies: A Survey and a Novel Knowledge-Based Taxonomy. Sensors 2021, 21, 568. https://doi.org/10.3390/s21020568

- V. C. F. da Costa, L. Oliveira, and J. de Souza, "Towards A Taxonomy for Ranking Knowledge in the Internet of Everything," 2021 IEEE 24th International Conference on Computer Supported Cooperative Work in Design (CSCWD), 2021, pp. 775-780, doi: 10.1109/CSCWD49262.2021.9437857.

- V. C. F. d. Costa, L. F. Oliveira and J. d. Souza, "A collaborative approach to support interoperability and awareness of the Internet of Everything (IoE) enablers," 2021 IEEE 2nd International Conference on

Human-Machine Systems (ICHMS), 2021, pp. 1-6, doi: 10.1109/ICHMS53169.2021.9582657.

- Farias, V.; Oliveira, L.M.L.; Souza, J. Internet of Everything Taxonomy: Technical Report of IoE Applications. Federal University of Rio de Janeiro: Systems Engineering and Computer Science Program. Available online: https://www.cos.ufrj.br/index.php/pt-BR/publicacoes-pesquisa

1.6 Structure

This thesis proposal is organized into five chapters. In the first one, motivations, research problem and questions, and the followed research methodology are presented. The remainder of this work is organized as follows:

Chapter 2 presents a theoretical background. First, the Theoretical Background of the thesis includes the Internet of Everything and other related paradigms, a literature review about smart sensors and KM, a study about IoE Governance, IoE Autonomic Computing, Service Science, and Serendipity in IoE, and related works for this research.

Chapter 3 presents the studies conducted in the conceptual phase to characterize and support the present research. A literature review about IoE and IoT taxonomies and the proposed IoE Knowledge-based Taxonomy is presented in detail. An IoE Integrated Knowledge Management Model is presented in Section 3.4. In Section 3.5, a literature review on smart sensors in IoE revealed requirements for smart sensors. Section 3.6 presents the IoE Database as a technological solution to support the curation of IoE enablers.

Chapter 4 discusses how these artifacts were evaluated. Finally, Chapter 5 presents the final considerations, objectives achieved, the contributions of the thesis and limitations of the work, and future research.

2 Theoretical Background

This Chapter presents the Theoretical Background of the thesis and is divided into eight subchapters or sections. The first one includes the Internet of Everything and related paradigms. In the second and third ones, a literature review about smart sensors and an investigation of knowledge management state of art and trends. Finally, this work studies Service Science, Autonomic Computing, Serendipity, and Interoperability issues applied to IoE.

2.1 Internet of Everything (IoE)

Internet of Everything (IoE) is a term that was first defined by CISCO in 2012 (EVANS, 2012) as a network of networks that brings together people, processes, data, and things to make network connections more relevant and valuable than ever before (AUGER; EXPOSITO; LOCHIN, 2018; CHARMONMAN; MONGKHONVANIT, 2015; YU *et al*., 2018).

IoE's four individual components or 'pillars' are people (becoming nodes on the Internet), data (transformed into information to support intelligent decisions and the effective environment control), things (context-aware smart sensors placed on everyday items), and processes (relevant and value-added connections to deliver the right information at the right time in the appropriate way) (EVANS, 2012) (Figure 2).

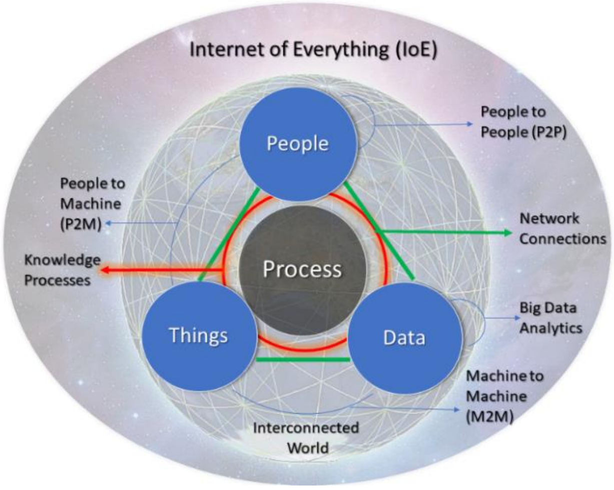


Figure 2. Four "pillars" in IoE (FARIAS DA COSTA; OLIVEIRA; DE SOUZA, 2021)

IoE expands on the IoT concept by connecting devices and people in one network (FIAIDHI; MOHAMMED, 2019). While the Internet of Things (IoT) is concerned about things (i.e., physical devices, accessed through the Internet), IoE lays an upper foundation over IoT and is concerned with intelligent network connections and technologies (BOJANOVA; HURLBURT; VOAS, 2014; DI MARTINO *et al.*, 2018a; SRINIVAS; JABBAR; NEERAJA, 2018; VAYA; HADPAWAT, 2020).

IoE extends the concept of IoT by going beyond things and integrating the societal impacts and benefits of a more interconnected world. Thus, "intelligent services", together with the "things", represent the "everything" in IoE (AUGER; EXPOSITO; LOCHIN, 2018)(GHOSH; CHAKRABORTY; LAW, 2018).

IoE supports creating new capabilities, richer experiences, and unprecedented economic opportunities for businesses, individuals, and countries (EVANS, 2012). With more relevant connections than IoT, IoE has enabled the global democratization of skills, including P2M, M2M, and P2P connections (RAJ; PRAKASH, 2018; SRINIVASAN *et al.*, 2019).

For Raj and Prakash (RAJ; PRAKASH, 2018), the IoE paradigm is a superset of IoT and requires advanced capabilities within the area of information sharing. It extracts and analyzes real-time data collected from diverse and heterogeneous environments, from simple sensors and actuators to complex robotic devices, and from autonomous service agents to human actors (YU *et al.*, 2018). Thus, IoE applications require appropriate measures to be taken in the initial phases of their design and implementation

(RAJ; PRAKASH, 2018). The devices must use Artificial Intelligence (AI) to comprehend how people process information and interact appropriately within a social context and multi-user scenarios, due to the increasing deployment of various novel, innovative, and useful IoE-based applications (MIRAZ *et al.*, 2018).

As will be discussed in Section 2.2, about IoE KM, actions and interactions within the IoE environment create and expand knowledge (NONAKA; TOYAMA, 2015) (JENNEX, 2017a), and when combined with human sensors' knowledge (tacit knowledge), this transformation from data to information in IoE provides essential insights and a wide variety of possible applications (DI MARTINO *et al.*, 2018b; ROY; CHOWDHURY, 2017).

A knowledge-based strategy for identifying decision support artifacts (big data, data, information, knowledge, and intelligence) assists in the management and governance of data and technologies to ensure great benefit from IoE's capacity to provide enhanced intelligent services.

So, IoE is calling for a new and open approach, to foster knowledge flows. New technologies emerging in the context of IoT and IoE are changing the way knowledge is managed within organizations and in people's daily lives. This scenario requires a specific knowledge management strategy and a specific approach which will be addressed in this thesis in Chapter 3.

2.1.1 Internet-based paradigms

Many Internet-based paradigms are under the IoE umbrella. Pliatsios *et al.* (PLIATSIOS; GOUMOPOULOS; KOTIS, 2020) analyzed the evolution from the Internet of Things (IoT) to the Semantic Social Network of Things (SSNT). For De Amorin and Braga (DE AMORIM SILVA; BRAGA, 2020), the Internet of Anything (IoA) is defined as an ubiquitous software ecosystem able to integrate IoT-derived systems. Over these networks, people usually create content developing a social network termed the Internet of People (IoP) (AZAD *et al.*, 2021) (NING *et al.*, 2021).

IoT concept focuses on the network layer, where things are harmoniously connected and communicate through the Internet to deliver services to end-users. In a technology-driven approach, several paradigms realize information interaction, such as Narrow Band Internet of Things (NB-IoT) which uses cellular wireless transmission

(BAOCHENG; SHAN, 2020). The Internet of Tangible Things (IoTT) refers to tangible interactions applied through IoT (GENNARI; MELONIO, 2019). Internet of Nano Things (IoNT) is the interconnection of nanoscale devices to communication networks, via electromagnetic radiations which are targeted towards a specific technology constraint-domain (in this case, nanotechnology) (PRAMANIK *et al.*, 2020). Internet of Mobile Things (IoMobT) serves as an example of design parameters strongly influencing communication and information processing (ANG; SENG, 2019). The Software-Defined Internet of Things-Fog (SDIoT-Fog) provides a new connectivity paradigm for effective service provisioning using network resource virtualization to provide services to heterogeneous IoT devices (KUMAR; TRIPATHI; P. GUPTA, 2021).

For Bennara *et al.* (BENNARA *et al.*, 2020) the advent of Web of Things (WoT) is an application layer for IoT. It associates data analysis and functionality to networked objects. Many paradigms under WoT umbrella concept relate to interoperability of multiple devices across different platforms and application domains with a common stack based on web services. Low Earth Orbit (LEO) mega-constellations have recently been proposed to offer broadband "Internet from Space", aiming to provide services comprising thousands of satellites (HAURI *et al.*, 2020). To enable IoT experience for existing products, the concept of an augmented product has been proposed where the Internet of Old Things (IoOT) uses actuators to replace human manipulation (CHO *et al.*, 2021). Green Internet of Things (GIoT) generally refers to a new generation of IoT design concepts composed of green smart devices (GSD), as a basic unit for saving energy (TAN, 2019).

Semantic Web of Things (SWoT) is considered a transformation of WoT by incorporating semantic web-based technologies within IoT, with the ability to exchange and use information among data and ontologies. A step forward from interoperability towards a collaborative IoT is the approach of Social Internet of Things (SIoT) where different devices create social relationships with each other (just like social relationships on a social network of people) (PLIATSIOS; GOUMOPOULOS; KOTIS, 2020).

In the Social Internet of Things (SIoT) paradigm, (DEFIEBRE; SACHARIDIS; GERMANAKOS, 2020) the connected objects operate autonomously to request and provide information and services to end-users. SIoT integrates the social concept into

IoT systems for enhancing service efficiency, by establishing a social relationship among smart objects free from human intervention (WEI *et al*., 2021).

Pliatsios *et al*. (PLIATSIOS; GOUMOPOULOS; KOTIS, 2020) proposed the concept of Semantic Social Network of Things (SSNT), “a network of things that 'speak', 'behave', 'collaborate' and 'coexist' just like a 'social network' of people”.

A Social Collaborative Internet of Things (SCIoT) is another paradigm that has strong ties with the Social Internet of Things (SIoT). It is defined as a platform of IoT where smart objects work together socially through recursive knowledge interactions and establishing social relationships with their surroundings. In this paradigm, smart objects aim to achieve common/shared goals on “behalf of humans” (KHAN *et al.*, 2017).

In Internet-of-Ships (IoS), objects (ships, crews, cargoes, onboard equipment, waterway environment, waterway facilities, shore-based facilities, and other navigation elements) are embedded with sensor and heterogeneous network technologies to boost the shipping industry towards improved safety, efficiency, and environmental sustainability (ASLAM; MICHAELIDES; HERODOTOU, 2020). Internet of Planets (IoP) aims at planets in the solar system, communicating with each other using the Internet (KANG *et al.*, 2021). The Internet of Multimedia Things (IoMT) paradigm is specialized in services and applications based on multimedia data (GATI *et al.*, 2021). Internet of Drones (IoD) provides coordinated access to controlled airspace for unmanned aerial vehicles (UAVs), also known as drones (WAZID *et al.*, 2020). Internet of Vehicles (IoV) and the Multimedia Vehicular Ad hoc Network (VANET) have attracted extensive attention from academia, industry, and government (LV; QIAO; SONG, 2020). The Internet of Health Things (IoHT) plays an increasingly important role in the collaborative development of regional medical services (TANG; WANG, 2020).

Internet of Underwater Things (IoUT) establishes intelligent interconnection of underwater objects and employ heterogeneous underwater sensor nodes with diverse underwater communication technologies, for sensing their surroundings and improving smart ocean awareness (QIN *et al.*, 2020) (BUSACCA *et al.*, 2020) (COUTINHO; BOUKERCHE, 2019).

With the advancement of technologies like network virtualization, mobile edge network, and software-defined network (SDN), software solutions implemented in IoT environments are termed as Internet of Softwarized Things (IoST) (SRIVASTAVA *et al*., 2021).

As part of smart ecosystems, the Enterprise Internet of Things (E-IoT) allows users to integrate and control more complex installations of audio, video, scheduled events, shades, door access, and relays via available user interfaces (RONDON *et al.*, 2021). The Internet of Musical Things (IoMusT) is an emerging research field to apply IoT in music technology, human-computer interaction, and artificial intelligence (TURCHET, 2019). Education IoT (EIoT) can be described as the interactive framework in the educational field where information is connected and synchronized by applying cloud computing, third-party technologies, gateways, and data communication (HUNG; WU, 2019).

Huang et al. (HUANG *et al.*, 2019) refers to the "everything is service" trend, forming "Service Internet" which is implemented as integrated services across domains and networks around the world. But further research is needed in terms of cross-domain service aggregation, value perception, and service intelligent interaction.

Ang and Seng (ANG; SENG, 2019) summarized the latest developments of Application-Specific IoTs (ASIoTs) (a term to conceptualize the development of IoT targeted toward specific domains): The Internet of Battle Things (IBoT) is designed for military and defense applications. Internet of Medical Things (IoMT) is a user domain-driven Internet-based paradigm for healthcare and patient monitoring. On the Internet of Animal Things (IoAT), smart objects and devices are used to monitor living creatures (e.g. livestock such as dairy cows, sheep, cattle) within the IoT. The Internet of Waste Things (IoWT) or Internet of Bins (IoB) includes smart garbage bins (SGBs) deployed in smart cities. The Internet of Underground Things (IoUGT) is targeted for underground network communications and is particularly useful for applications in environmental monitoring. The Internet of Robotic Things (IoRT) and its fusion with deep learning techniques are applied in multiple application domains (ANTENUCCI *et al.*, 2021). Internet of Vehicles (IoV) is focused on vehicles connectivity, consisting of a subarea of IoT applied to automobiles (FRANÇA *et al.*, 2021).

The Cognitive Internet of Things relates to collective AI, based on autonomous software agents, things that can sense, think and act within IoT (ANASTASIOU *et al.*, 2020).

IoT trend applied to the industrial sector is commonly referred to as Industry 4.0, i.e., the fourth industrial revolution, or as Industrial Internet of Things (IIoT) (SERROR et al., 2021). The Internet of Production (IoP) envisions the interconnection of previously isolated cyber-physical systems (CPS) enabling computer systems to (remotely) execute control over entities in the manufacturing physical world across institutional boundaries (PENNEKAMP *et al.*, 2019).

Figure 3 presents the evolution route to the IoE paradigm, related to smartness and relevance in network connections. Moving upwards to the IoE paradigm, IoE is more than the approach to connect human social networks in the Social Internet of Things (SIoT). While Web of Things (WoT) adapts existing web technologies to build new applications and services, Semantic Web of Things (SWoT) focuses on machine-understandable data and in the description of data with common vocabularies.

IoE represents network "connections" and real-time data/information flows (LANGLEY *et al.*, 2020) among IoE nodes (MIRAZ *et al.*, 2015). The result is smartness and intelligence (MASOUD *et al.*, 2019), and real-time insights working in concert (VANDEBROEK, 2016), far beyond IoT context disruptions (MAJEED, 2017), addressing the societal and organizational needs for more data and more actionable intelligence.

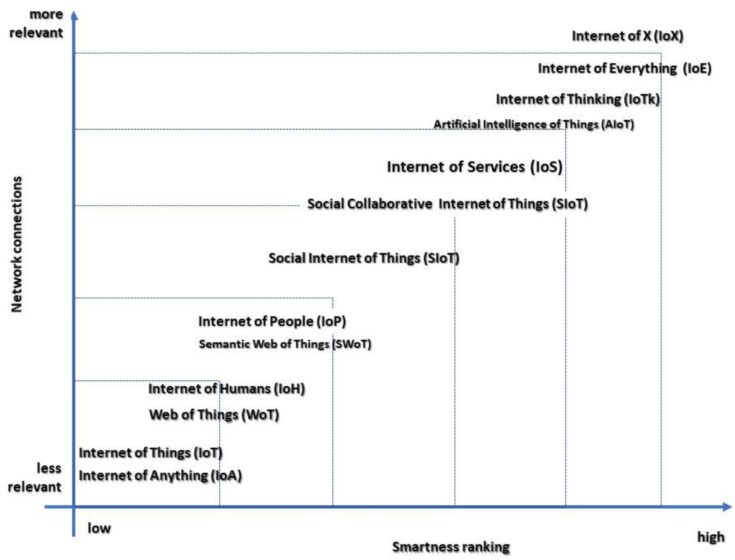


Figure 3. The evolution route from IoT to IoE (prepared by the author)

Ning *et al.* (NING *et al*., 2021) proposed a novel concept called the Internet of X (IoX). This Internet-based paradigm represents the integration of traditional IoT infrastructure with the Internet of People (IoP) and the brain-abstracted Internet of Thinking (IoTk), which aggregates AI for intelligent interconnections. In this paradigm, all things, entities, people, and thinking benefit from both space convergence and ubiquitous connections. To justify their attempt to introduce the novel concept of the Internet of X (IoX), authors presented a limited interpretation of IoE as "*it mainly emphasizes the phenomenon of connecting the unconnected*".

Another restricted understanding of IoE paradigm disruption is presented by Lohiya and Thakkar (LOHIYA; THAKKAR, 2021) following the idea that IoT evolves to the "Internet of Everything" when it incorporates advanced technologies (wireless networks, sensors, cloud servers, analytics, smart devices) with machine-to-machine interactions only to "empower people".

A recent paradigm "the metaverse" refers to a virtual world where avatars (user's alter ego) acts, engage in political, economic, social, and cultural activities between virtual reality and reality (PARK; KIM, 2022). It is strengthened with mobile-based always-on access to connectivity with reality using virtual currency.

Providing a broad, comprehensive, and updated view of the IoE paradigm is, in fact, the main contribution of this thesis. This work proposes an IoE taxonomy based on knowledge and resource management in the IoE context, to address intelligence services issues through a knowledge-based strategy approach.

Figure 4 shows the characterization of the IoE paradigm in a Venn diagram, showing diverse intersections between other internet-based paradigms presented in the literature:

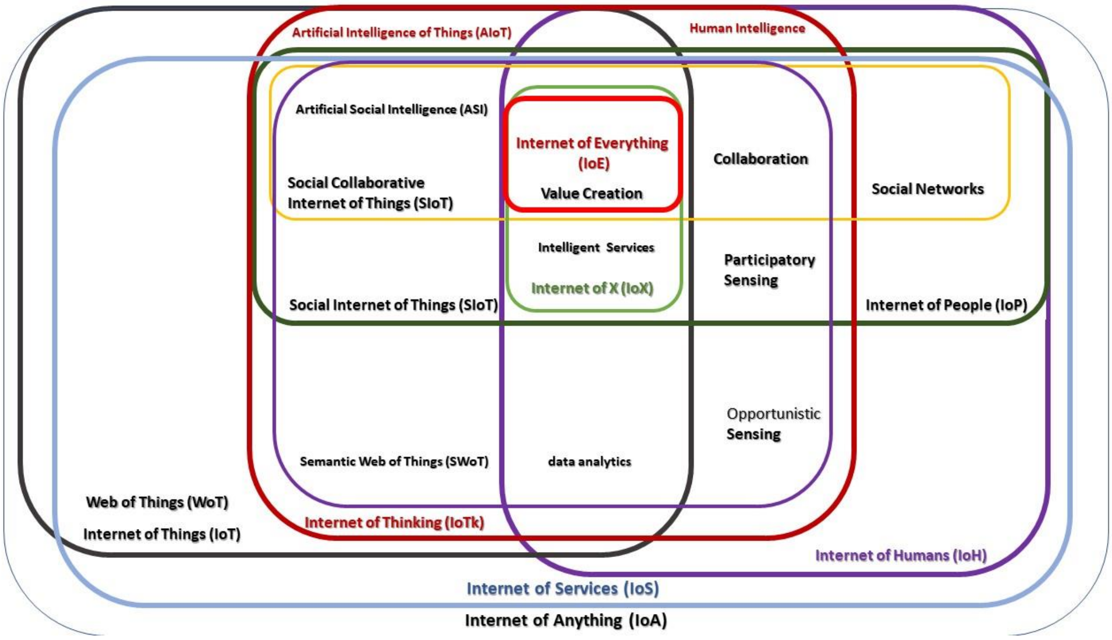


Figure 4. IoE Venn Diagram (prepared by the author)

2.1.2 Uncovering the IoE paradigm

Although recent works are like this thesis approach in terms of coverage and analysis of the IoE paradigm, some approaches only deal briefly upon knowledge creation and collaboration among IoE devices; while others propose taxonomies to uncover IoE and IoT paradigms concerning specific areas (e.g., observations, infrastructure, sensor type, and analytics for IoT and IoE). Previous works design challenges from several perspectives; however, they do not explicitly address the characteristics of knowledge types provided by knowledge enablers (sensors and actuators) and how IoE sensors collaborate to improve efficiency in IoE solutions. In general, the identification of knowledge sources in human and non-human sensor nodes requires a holistic and multidisciplinary approach. And for knowledge-intensive IoE applications, the identification of knowledge sharing in human-machine relationships is still mostly inadequate.

However, there are challenges concerning the ranking and managing of knowledge processes in IoE applications. Recent studies have addressed different research challenges in IoT areas, and several authors have proposed taxonomies for dealing with IoE and IoT systems, in specific following focus and approach:

- **Technology and architecture design:** (BELLAVISTA; BERROCAL, 2019; GLUHAK *et al.*, 2011; HALLER *et al.*, 2013; HARON *et al.*, 2017; MARJANI *et al.*, 2017; PERERA *et al.*, 2014)
    - Yaqoob et al. (YAQOOB *et al.*, 2017) proposed an end-to-end view taxonomy to categorize and classify IoT architectures, considering parameters such as applications, enabling technologies, business objectives, architectural requirements, network topologies, and IoT platform architecture types.
    - Haller et al. (HALLER *et al*., 2013) have focused on central concepts and their relationships in the IoT domain, considering IoT as a self-configuring, adaptive, complex network that interconnects "things" to the Internet, through standard communication protocols (ALKHABBAS; SPALAZZESE; DAVIDSSON, 2019).
    - In Mountrouidou *et al.* (MOUNTROUIDOU; BILLINGS; MEJIA-RICART, 2019), the authors characterized IoT based on generic building blocks or primitives, defining IoT devices as sensing or actuating devices that can communicate with other devices and perform specific functions.
- **Sensors' capabilities:** (BHATT; PATWA; SANDHU, 2017; DORSEMAINE *et al*., 2015; FORTINO *et al.*, 2014; MOUNTROUIDOU; BILLINGS; MEJIA-RICART, 2019; OBINIKPO; KANTARCI, 2017; SHAHID; ANEJA, 2017)
    - Shahid and Aneja (SHAHID; ANEJA, 2017) proposed an IoT taxonomy, developing technologies and solutions for enabling IoT vision, which is related to smart objects' ability to communicate and interact, either in building networks of connected items or with end-users or other entities in the network.
    - Obinikpo and Kantarci (OBINIKPO; KANTARCI, 2017) presented a taxonomy of methodologies based on types of sensors and sensed data. Other works have proposed taxonomies to categorize the IoT's connected

objects, devices, and smart objects (BHATT; PATWA; SANDHU, 2017; DORSEMAINE *et al.*, 2015; FORTINO *et al.*, 2014).

  - To support the development process of smart objects, specifically in the design phase, Fortino et al. (FORTINO *et al*., 2014) proposed a reference taxonomy for smart objects that is functional for service discovery.
  - Agarwal et al. (AGARWAL *et al.*, 2016) reused concepts from several "third-party" ontologies and taxonomies and proposed a taxonomy for heterogeneous IoT testbeds, called FIESTA-IoT. It combines existing IoT ontologies into minor updates to overcome the most common issues associated with mainstream ontologies.

- **Observation context issues:** (ASGHARI; RAHMANI; JAVADI, 2018; BUGEJA; DAVIDSSON; JACOBSSON, 2018; CHEN; HELAL, 2011; ERIS; DRURY; ERCOLINI, 2015; NOURA; ATIQUZZAMAN; GAEDKE, 2019; OBERLÄNDER *et al.*, 2018; SETHI; SARANGI, 2017; SHOLLA; NAAZ; CHISHTI, 2017; YAQOOB *et al.*, 2017)
  - Noura et al. (NOURA; ATIQUZZAMAN; GAEDKE, 2019) developed a taxonomy for IoT interoperability issues related to the following heterogeneity challenges in IoT environments: device interoperability, networking interoperability, syntactic interoperability, semantic interoperability, and platform interoperability.
  - In (ASGHARI; RAHMANI; JAVADI, 2018), the authors proposed a technical taxonomy for service composition in the IoT environment, based on functional and non-functional aspects.
  - Bugeja et al. (BUGEJA; DAVIDSSON; JACOBSSON, 2018) proposed a classification model based on the functionality of smart home devices.
  - Oberländer et al. (OBERLÄNDER *et al*., 2018) contributed to the IoT's descriptive knowledge and presented a classification of business-to-things interactions to facilitate sense-making and theory-led design.

- **Management solutions for control of IoT systems**:
  - Sinche et al. (SINCHE *et al.*, 2019) proposed a taxonomy for IoT device management.

- Perera et al. (PERERA *et al.*, 2014) surveyed a broad range of techniques, methods, models, functionalities, systems, applications, and middleware solutions related to context awareness and IoT.
- Püschel et al. (PÜSCHEL; ROEGLINGER; SCHLOTT, 2016) presented a multi-layer taxonomy of smart things. It comprises ten dimensions structured within architectural layers of existing IoT stacks (i.e., the thing itself, interaction, data, and services). The classifications are continuously re-evaluated and adjusted to account for upcoming smart things.

- **Security in the adoption of IoT technologies and applications:** (CHEN; HELAL, 2011)
  - Ashraf and Habaebi (ASHRAF; HABAEBI, 2015) proposed a taxonomy that aims to group IoT security vulnerabilities and their mitigation solutions.
  - Haron et al. (HARON *et al.*, 2017) proposed a taxonomy of data trustworthiness for IoT sensor data. Alsamani and Lahza (ALSAMANI; LAHZA, 2018) studied the relationship between object characteristics, security, and privacy, and they proposed a taxonomy to categorize potential security threats in IoT.
  - In (ZHANG *et al.*, 2018), the authors presented a comprehensive analysis of data security and privacy threats, protection technologies, and countermeasures inherent in edge computing.
- **Network architecture for IoT:**
  - Gluhak et al. (GLUHAK *et al.*, 2011) provided a taxonomy for the scope and architecture of testbeds in the IoT.
  - Naha et al. (NAHA *et al.*, 2018) proposed a taxonomy considering the requirements of the fog computing paradigm.
  - In Hassan et al. (HASSAN *et al.*, 2018), a taxonomy of edge computing classifies and categorizes existing edge computing paradigms for IoT.
  - Ahad et al. (AHAD; TAHIR; YAU, 2019) provided a state-of-art review of 5G- and IoT-enabled smart healthcare.

- Oteafy and Hassanein (OTEAFY; HASSANEIN, 2019) proposed a taxonomy of edge-IoT systems designed for rapid data acquisition.
- Bellavista and Berrocal (BELLAVISTA; BERROCAL, 2019) presented an unified architectural model and proposed a new taxonomy after comparing solutions that had emerged for supporting the requirements of IoT applications.

- **Effective collaboration process between smart devices:**
  - A comprehensive look at IoT environment collaboration is presented in (ERIS; DRURY; ERCOLINI, 2015), in a taxonomy to clarify how IoT enables collaboration.
  - People (as customers) and applications are perspectives that nurtured the IoT taxonomy presented by Smutný (SMUTNÝ, 2016).
  - Salim and Haque (SALIM; HAQUE, 2015) proposed a taxonomy for categorizing and characterizing urban computing technologies, and also discussed the level of participation these technologies stimulate in modern society.
- **Integrating humans in the loop:** (ARMANDO *et al.*, 2018)
  - Sholla et al. (SHOLLA; NAAZ; CHISHTI, 2017) argue that integrating socio-cultural and ethical aspects within a smart city architecture turns it into a people-friendly environment.
  - Hui and Sherratt (HUI; SHERRATT, 2017) discussed how to stimulate human senses and capture human responses, and proposed a novel taxonomy for disappearing user interfaces.
  - Yebda et al. (YEBDA *et al*., 2019) reviewed existing solutions for social sensing.
  - Phuttharak and Loke (PHUTTHARAK; LOKE, 2019) presented a taxonomy based on the critical issues in mobile crowdsourcing.
  - Chaochaisit et al. (CHAOCHAISIT *et al.*, 2016) presented an ontology for human localization sensors to address challenges in searching for users' location-aware sensors.

- Sethi and Sarangi (SETHI; SARANGI, 2017) proposed a novel taxonomy for IoT technologies and profiles and some applications that have the potential to make a striking difference in human life.

- **Information flow, quality of data, and opportunities in big data analytics:**
  - Bisdikian et al. (BISDIKIAN; KAPLAN; SRIVASTAVA, 2013) presented a framework for scoring and ranking information products based on their value of information attributes.
  - Agarwal et al. (AGARWAL *et al.*, 2016) proposed an ontology for reusing and interconnecting existing ontologies.
  - Shah et al. (SHAH *et al.*, 2019) created a thematic taxonomy for deploying these solutions collaboratively to provide guidelines for harvesting, transmitting, managing, and analyzing disaster data from various data sources, to deliver valuable up-to-date information to support disaster management environments.
  - (RISTOSKI; PAULHEIM, 2016), (QANBARI *et al.*, 2015), and (ROZSA *et al.*, 2016) proposed semantic web techniques for better representation and exploration of sensor data.
  - Qanbari *et al.* (QANBARI *et al.*, 2015) incorporated semantic and linked data technologies to increase data quality.
  - In (ROZSA *et al.*, 2016), Rozsa *et al.* presented a taxonomy that identifies and categorizes sensors as the source devices to provide publication, discovery, sharing, reuse, and integration of data/information.
  - Marjani *et al.* (MARJANI *et al.*, 2017) explained the relationship between big data analytics and IoT and proposed a new architecture for IoT big data analytics.
  - Yaqoob *et al.* (YAQOOB *et al.*, 2016) surveyed the domain of big data by examining the different techniques utilized for data processing and analytics.
  - Gao *et al.* (GAO; LEI; YU, 2015) presented a taxonomy of big data sensing and services. And Ge *et al.* (GE; BANGUI; BUHNOVA, 2018),

and surveyed big data technologies that stimulate knowledge sharing across IoT domains.

- Subbu and Vasilakos (SUBBU; VASILAKOS, 2017) discussed the latest developments in the big data sensing field applied to context-aware big data systems.
- Moustaka *et al.* (MOUSTAKA; VAKALI; ANTHOPOULOS, 2018) proposed a taxonomy to integrate data science and smart city domains by focusing on principles related to urban data sources and analytics approaches concerning data harvesting and data mining processes.
- Langley *et al.* (LANGLEY *et al.*, 2020) developed a vision of how the IoE may alter business models and how individuals and organizations create value and proposed a taxonomy to compare different IoE applications with benchmarks of IoE ecosystems.
- For Haron *et al.* (HARON *et al.*, 2017), the decision-making process in the IoT domain relies entirely on the data. The authors proposed a not exhaustive taxonomy of Data Trustworthiness for IoT Sensor Data based on the extant works.
- Sharma *et al.* (SHARMA *et al.*, 2018) proposed a cognitive artificial system that computationally generates models of abstract concepts and representation of data obtained from IoE sources such as people, things, or processes.

- **Mobility and localization:**
  - Shit *et al.* (SHIT *et al.*, 2018) proposed a hierarchical taxonomy of the localization technique based on offline localization training, namely self-determining and training-dependent approaches.
  - Saad *et al.* (SAAD; ELHOSSEINI; HAIKAL, 2018) presented a taxonomy that classifies variant localization algorithms.
  - Pozza *et al.* (POZZA *et al.*, 2015) made a classification between mobility-agnostic and mobility-aware discovery protocols.
  - Berger *et al.* (BERGER; DENNER; RÖGLINGER, 2018) developed a multilayer taxonomy of digital technologies that includes eight structured

dimensions along with the layers of established modular architectures (i.e., service, content, network, and devices).

Despite the vast coverage of research areas and focus, an integrated perspective of IoE enablers is still a research gap: the human-thinking perspective integrated into IoE is still missing; the taxonomies have scope limitations due to the high heterogeneity of existing IoT devices; the seldom investigation of how collaboration throughout sensors and actuators of different types create value in cyberspace; the restricted investigation of interactions between human sensors and smart sensors for knowledge sharing.

Few works have investigated the whole of human sensors in a smart environment and how things interact with human sensors through knowledge processes that lead to actionable intelligence. The critical goal of integrating human actors is to develop proper interfaces based on application domains, the type of operation to be performed, and integration between human sensors within the whole system (SAHINEL *et al.*, 2019).

As the world is running on the advent of the IoE lifestyle (FARIAS DA COSTA; OLIVEIRA; DE SOUZA, 2021) (GADDAM *et al.*, 2020), IoT infrastructure provide increased communication capability, IoE's success in penetrating all dimensions of IoE lifestyle heavily depends on processing, storing and extracting “sense” from the exponentially growing amount of structured and unstructured, data in real-time and guarantee the interoperability posed by the interaction between “everything” (JESSE, 2018). As in a collaborative workspace (GUTWIN; GREENBERG, 2004), humans must maintain situational awareness to work collaboratively with smart sensors. And smart sensors (things) understand people's requirements to enhance the value chain autonomously and support intelligence services (RHO; CHEN, 2018).

In a broad manner, recent studies do not categorize and organize IoE in a concise manner which provides a contextual understanding of the complexity of IoE enablers. As one of this thesis contributions, Chapter 3 will present a comprehensive knowledge-based IoE taxonomy that organizes tangible and intangible elements as integrated resources and drives knowledge creation in IoE disruptive environment.

2.2 Smart sensors in IoE

Smart sensors are crucial in every IoE application (smart cities, smart grid, health care, agriculture, security, and environment monitoring, and smart parking) as they bridge the world's physical objects with the cyber world of IoE (RAYES; SALAM, 2017). They are equipped with artificial intelligence (AI) to provide the deployment of innovative IoE-based applications, where people (as human sensors) and things (sensors and actuators) interact appropriately within a social context and multi-user environment (MIRAZ; ALI; EXCELL, 2015), a phenomenon defined as "smart revolution" (JANEERA *et al.*, 2021). In this context, things are defined as physical smart sensors which provide a direct perception of the environment to achieve a task (KOLAR; BENAVIDEZ; JAMSHIDI, 2020)(ALONSO *et al.*, 2020a).

A challenge in this domain is to support the control and orchestration of "smart" sensors (things and people) and their enabling intelligence embedded in smart systems (BERTOLI *et al.*, 2021)(MCLAMORE *et al.*, 2019).

In some cases, smart sensors in IoT networks are deployed in harsh environments, contributing to sensors failure, malfunction, malicious attacks, theft, and tampering. To ensure the quality of sensed data collected and avoid outliers (unusual and erroneous readings), the data collected by sensors are initially pre-processed to be transformed into information and further processed into applications and processes, with aid of artificially intelligent (AI) and machine learning (ML) models (SAAD; ELHOSSEINI; HAIKAL, 2018).

For Metallidou *et al.* (METALLIDOU; PSANNIS; EGYPTIADOU, 2020), smart sensors support M2M and H2M interactions and value creation. Bacciu *et al.* (BACCIU *et al.*, 2017) studied the adoption of heterogeneous smart devices (sensors and actuators) that are pervasively collecting information through the interaction with humans in their environment (ABDEL-BASSET *et al.*, 2020). The adoption of machine learning (ML) methodologies allows smarter IoT applications to continuously adapt to evolving environmental conditions and users' needs.

Bertoli and Fantuzzi (BERTOLI *et al.*, 2021) studied smart sensors orchestration in cyber-physical systems to address deep integration of computing, communication, and process control, with humans in the loop. Their work mainly focused on the area of data mining and data interpretability and analysis.

For Pundir and Sandh (PUNDIR; SANDHU, 2021), there are specific Quality of Services (QoS) mechanisms used in the field of smart sensors, due to its dynamic and resource constraint nature: including throughput, packet loss, latency, delay, security, scalability, jitter, maintainability, packet error ratio, availability, reliability, priority, periodicity, dead-line, bandwidth, and energy consumption.

The combination of sophisticated sensors and increased computational power will enable new ways to analyze data and gain actionable insights in industries (AHELEROFF *et al.*, 2020), factories, airports (KORONIOTIS *et al.*, 2020), parking spaces (SAARIKA; SANDHYA; SUDHA, 2018), households, and workplaces (GUPTA, 2021).

Recent interest has mainly focused on the concepts of cyber-physical systems (CPS) or the Internet of Things (IoT) with applications to smart city and smart grid concepts (PETRARIU; COCA; LAVRIC, 2021). Yaseer and Chen (YASEER; CHEN, 2021) reviewed the latest sensor technologies and machine learning techniques that can be used as a decision support tool for making the animal farming process more profitable and insightful. In the human-animal iterations field, smart sensors monitor the animals' health, location, behavior, and/or environment. (JUNIOR, 2020)

IoT places a relevant role in health monitoring (SHARMA; CHOUDHURY; KUMAR, 2018) with wearable smart biosensors and body sensors for monitoring patients (TAMILSELVI *et al.*, 2020)(FIROUZI *et al.*, 2018).

Smart farming (YANG; SHARMA; KUMAR, 2021) is another promising application area that uses smart sensors and communication technologies to support intelligent decision-making systems to facilitate the agricultural sector (IoT-Agro) (PACHAYAPPAN; GANESHKUMAR; SUGUNDAN, 2020). To minimize the cost, maintenance, and monitoring of farms, traditional agriculture methods will be gradually replaced by smart technologies (MANOGARAN *et al.*, 2021) in IoT farm networks (ASTILL *et al.*, 2020).

For Suresh *et al.* (SURESH; UDENDHRAN; BALAMURUGAN, 2020) integrating IoT and machine learning (SURESH; UDENDHRAN; BALAMURUGAN, 2020) will be reflected on many aspects of human life in all segments. Surveillance system applications are drastically growing from small areas (buildings and homes) to wide areas such as forest monitoring. In smart home automation solutions (PATCHAVA; KANDALA; BABU, 2017), IoT smart sensors capture intruders' identities and detect their presence, whenever motion is detected. Smart sensors embedded into systems performs real-time monitoring based on a deep learning model in a smart waste management solution (SHENG *et al.*, 2020). And so smart sensors have been deployed in surveillance system applications to monitor and record forest environmental impacts and safety production (YUAN *et al.*, 2020). Abnormal events are identified and detected using appropriate IoT smart devices and deep learning algorithms (CUI, 2020).

The adjustment of industrial production to complete intelligent automation in Industry 4.0 (KARABEGOVIĆ *et al.*, 2020), introduces new technological discoveries and intelligent decision-making. For Elsisi *et al.* (ELSISI *et al.*, 2021), smart grids are control infrastructure that manages and monitors the communication between smart machines to increase efficiency in the industrial environment. Digital twins or surrogates are data-driven virtual representations that replicate, connect, and synchronize the operation of a manufacturing system or process (SHAO; KIBIRA, 2019).

It is difficult to enhance all parameters of QoS in IoE applications simultaneously such as improving communication and processing capabilities without impacts on energy consumption across the network. The focus for a trade-off between parameters to enhance the performance of IoE applications is related to value creation and expected outcomes, the core parameters for QoS in IoE. There is a need to introduce a knowledge-based driven approach to define domain-specific QoS related to intelligent services in IoE applications. This approach will be presented in Section 3.5, which will define smartness requirements for IoE smart sensors.

As of today, people’s public and private spaces are equipped with advanced technology, which is reshaping their lifestyles (WANG *et al.*, 2020). Services are sensor-collected-information driven and enhancing value creation through data is paramount. Often, these data are obtained from the environment where the information is up-to-date and can be accessed through either built-in or connected smart sensing devices (KOLAR; BENAVIDEZ; JAMSHIDI, 2020). The expansion of data connectivity is a “catalyst for divergent application of sensors” and a sustainable ecosystem lies in the creation of a bridge where “data play an important role as both a resource and as a tool” (NIKIFOROVA, 2021). Section 2.3 will discuss how KM addresses the challenge to cope with implicit and explicit knowledge in IoE ecosystems.

In Chapter 3, this thesis will apply the proposed IoE Knowledge-based Taxonomy as the main driver for investigating and defining requirements for smart sensors as IoE enablers, with a qualitative approach. Existing works on smart sensors are collected and classified into four categories of IoE Knowledge-based taxonomy. From this, possible future directions are proposed related to metrics and parameters for ranking knowledge in smart sensors in IoE applications and an evaluation approach will be presented in Chapter 4.

2.3 Knowledge Management in IoE Lifestyle

As defined in previous sections, the Internet of Everything (IoE) is a superset of the Internet of Things (IoT) by incorporating people, processes, data (CHARMONMAN; MONGKHONVANIT, 2015), and intelligence in the network (MIRAZ *et al.*, 2015). The knowledge created and derived from data adds 'value' and provides insights into the dynamic IoE context disruptions (MAJEED, 2017).

IoE paradigm consists of extracting and analyzing real-time data from millions of sensors and applying it to automated processes in opportunities for combining related sensors and data sources (SHEN; NEWSHAM; GUNAY, 2017). IoE sensors range from simple sensors and actuators to complex devices and from autonomous agents to human actors.

To research how knowledge management process research is applied to IoE, this thesis reviewed contributions from the ACM Digital Library, IEEE Digital Library, ISI Web of Science, Science@Direct, and Scopus databases, which were the most relevant sources for finding specific studies in journal and conference papers in English. The following specific search string was sought: ("knowledge management") AND ("internet") in the "Title", "Abstract", or "Keywords" fields. And restricted to studies since 2015 to support the novelty of the proposals.

The search string retrieved from the databases as many studies as possible that were relevant to the review, even if the query results returned articles not relevant to the survey. It is important to mention that the generic term “internet” was propositional to consider paradigms under the IoE umbrella such as “internet of things”, “internet of people”, “industrial internet” and so on, considering studies not explicitly related to IoE. Furthermore, most contributions were studies related to KM in IoT environments, which indicates a lack of maturity in work in the field of KM in IoE.

Only studies published in English in journals (already published and in press), conference proceedings, books, and technical reports were selected. After discarding the duplicates, a total of 715 candidate articles remained from the initial search (Table 1).

Table 1. Summary of literature review stages

Literature review stage	number of papers
Search of ISI Web of Science	231
Search of Scopus	174
Search of IEEE	335
Search of ACM Digital Library	70
Science@Direct	38
Total	848
Duplicates	133
Total after discarding duplicates	715
Discarded	542
Approval for analytical reading	173
Unclassified	134
Approved	39

The success of any knowledge management initiative in IoE disruption lies in its ability to cope with sharing of implicit and explicit information of “smart objects” (SO) and data sources in the IoE domain (TSAI *et al.*, 2014) – things and humans or broadly between biotic or abiotic sensors in IoE context. The challenge is to create value integrating knowledge of people as human sensors (SHEN; NEWSHAM; GUNAY, 2017). Optimum combinations of sensors and data sources need to be identified since many devices and resources in IoE are highly distributed, heterogeneous, and constrained. Therefore, a smart environment is capable of obtaining knowledge, applying it, or adapting according to its users' needs for creating value from the experience with that environment (AHMED *et al.*, 2016).

Knowledge Management (KM) processes are essential for improving the capabilities, successful adoption, and implementation of a particular technology (AL-EMRAN *et al.*, 2018), such as the novel paradigm of IoE applications. But there is still an opportunity for further research, calling for new and inventive knowledge management open approach, to foster knowledge flows, and to facilitate the creation of open and collaborative ecosystems (SANTORO *et al.*, 2017) applied to humans and things. And in terms of data, there is an opportunity to discover hidden knowledge and generate new knowledge with ultimate new demands from the digital era (KHAN; VORLEY, 2017).

A traditional knowledge pyramid originally proposed by Ackoff *et al.* (ACKOFF, 1989) defines that data are symbols that represent the properties of objects and events. The author concludes that information, knowledge, and understanding lead to increase efficiency, not effectiveness. And intelligence is the ability to increase efficiency, measured relative to an objective with a specified number of resources. The value of the objective(s) pursued is relevant in determining effectiveness. Effectiveness is evaluated efficiency. It is efficient for a valued outcome. Therefore, it is the ability to optimize the resources in IoE processes that leads to a determined objective and value creation.

Currently, with the increasing dissemination of IoE solutions, research efforts are being directed to the analysis of knowledge creation and wisdom. Barnaghi *et al.* (BARNAGHI *et al.*, 2012) revisited the traditional knowledge pyramid originally proposed by (ACKOFF, 1989) to explain the creation of actionable intelligence and knowledge and presented knowledge hierarchy layers applied to the context of IoT (Figure 5). The hierarchy layers refer from a large amount of data produced by the IoT resources and devices to high-level abstractions and perceptions (wisdom). However, their study does not provide a comprehensive analysis of how actionable intelligence and knowledge creation derive from the collaboration of humans and things in IoE solutions.

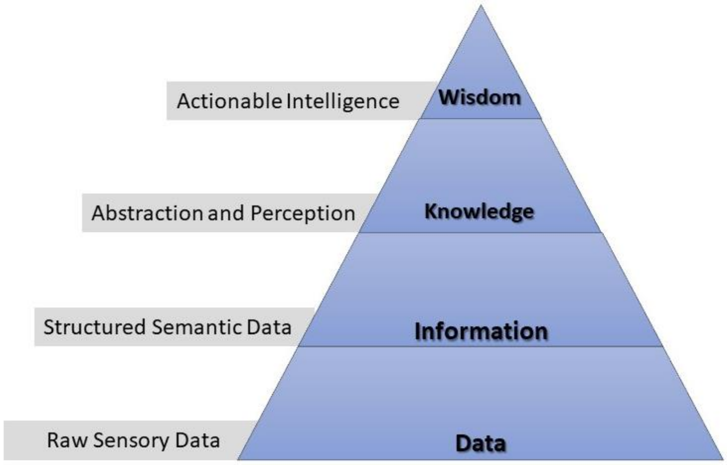


Figure 5. "Knowledge Hierarchy" in the context of IoT (Adapted from Barnaghi et al, 2012)

In Figure 6, a data approach of knowledge hierarchy layers in the context of IoT is proposed by Siow *et al.* (SIOW; TIROPANIS; HALL, 2018a). Big data solutions and cloud platforms provide infrastructure and tools for handling, processing, and analyzing overload of the IoT data. However, this data-to-knowledge transformation demands efficient methods and solutions to structure, annotate, share, and make sense of the IoT data and facilitate identifying, filtering, and transforming it to actionable knowledge and intelligence. Authors, related the knowledge hierarchy to five categories of analytics capabilities for IoT data (Figure 6), as follows (SIOW; TIROPANIS; HALL, 2018a):

- Description in Analytics: For describing, summarizing, or presenting raw IoT data that has been gathered.

- Diagnosis in Analytics: To find out the root cause and explanations for the IoT data. Both descriptive and diagnostic analytics provides hindsight on what and why things have happened.

- Discovery in Analytics: Through the application of inference, reasoning, or detecting nontrivial information from raw IoT data. It detects something new, novel, or different (e.g., trends, exceptions, or clusters) rather than describing or explaining it.

- Prediction in Analytics: It uses past data and knowledge to predict future outcomes and provides methods to assess the quality of these predictions.

- Prescription in Analytics: It presents the best course of action to act on foresight on time with the consideration of uncertainty.

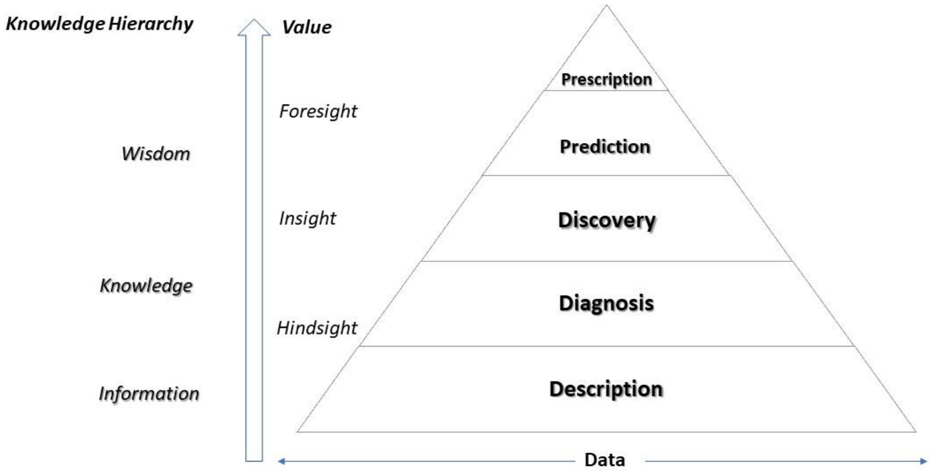


Figure 6. Analytics and the knowledge and value hierarchies, adapted from Siow et al. (2018)

In Figure 7, by turning the hierarchy of knowledge upside down, a revised knowledge pyramid in the context of IoT is proposed by (JENNEX, 2017b). The study reversed the knowledge pyramid by assuming that there is more knowledge than data and expanded it (from data to wisdom) in a broader context. Humans are constantly gathering and processing data into information, knowledge, and wisdom. This approach posits a top-down strategy that leads to efficient identification of data, information, and knowledge sources identifying the technologies and decision support components. A top-down KM strategy for managing the knowledge pyramid activities includes the identification of actionable intelligence needed to support societal decision-making and the effective use of actionable intelligence. The more focused the strategy, the stronger the filters that are created to support intelligent decision making, supported by relevant information selection.

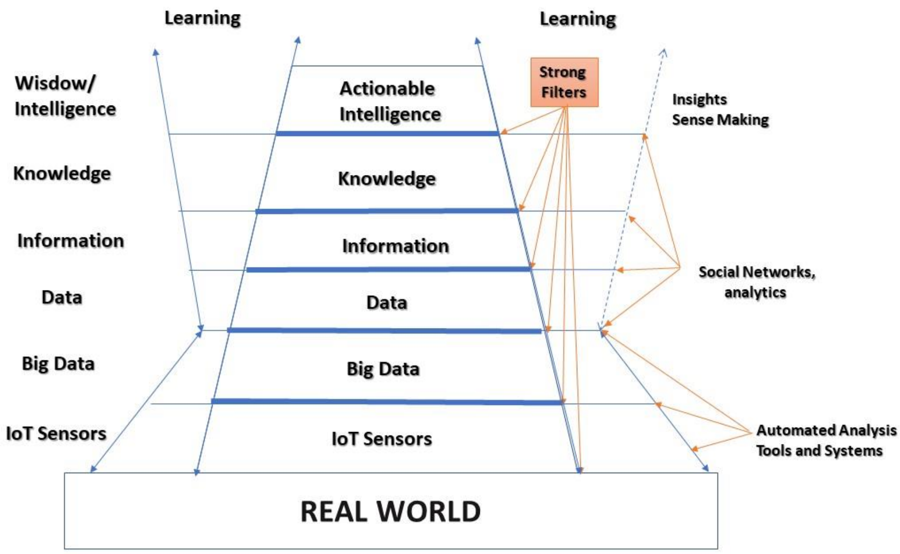


Figure 7. The Revised Knowledge Pyramid with KM, Big Data and IoT, adapted from Jennex, 2017b.

Knowledge creation involves not only organization and context but also integration and collaboration (FIORE *et al.*, 2010). A Social Collaborative Internet of Things (SCIoT) (KHAN *et al.*, 2017) is a new paradigm defined as an IoT platform, based on the collaboration of network objects for achieving a common goal. The collaboration of social objects is dependent upon the services they provide to benefit people in an intelligent network environment. Khan *et al.* (KHAN *et al.*, 2017) analyze a socially collaborative environment in IoT as a hierarchical knowledge pyramid (SCIoT pyramid) to represent the levels of collaboration for knowledge transformation.

In Figure 8, SCIoT pyramid is introduced to represent the levels of different processes of IoT collaborating environment, from raw data to service delivery. At the lowest level, intelligent sensors embedded in the smart objects collect raw data by monitoring the environment. Then, information is created by analyzing, processing, and reducing the raw data. After the information is analyzed, IoT objects get knowledge about a particular situation or a problem. After having detailed knowledge, IoT objects learn and communicate to share knowledge effectively. After communicating with other objects, IoE devices exchange and share their resources through cooperation. While cooperating, all the activities are arranged sequentially and are harmonized through coordination. After aligning the coordinated activities, these activities are performed effectively through proper collaboration. Smart objects collaborate through cooperation and coordination. The collaborated knowledge is then integrated through convergence. Finally, the service providers grant services to the service requester.

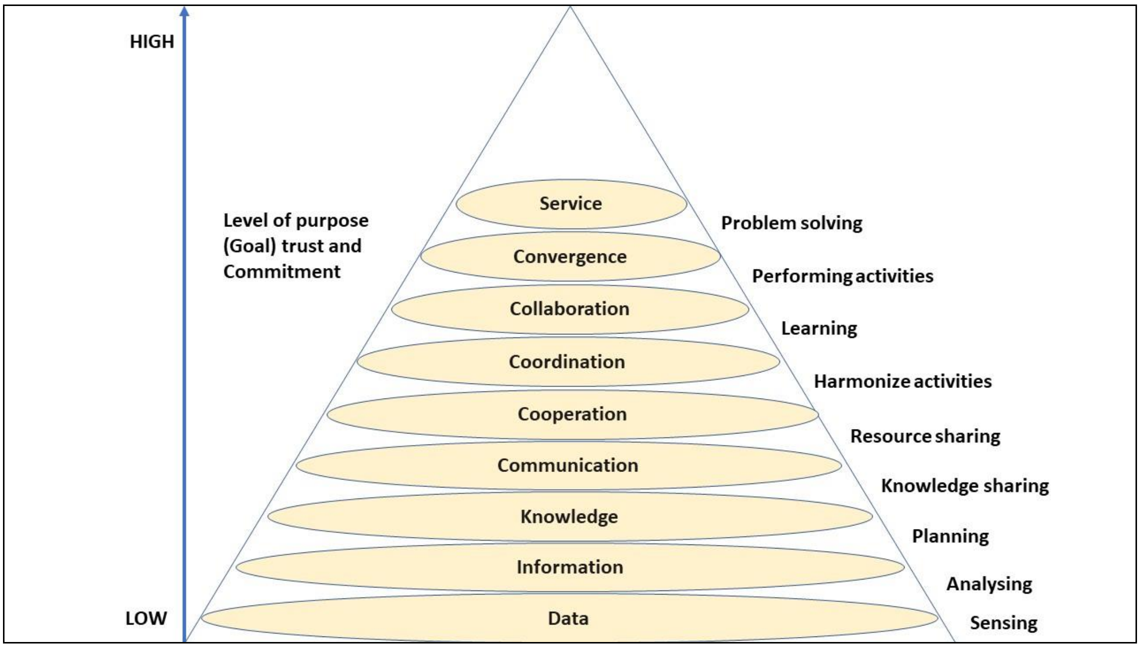


Figure 8. SCIoT pyramid, adapted from Khan et al., 2017.

Knowledge creation is a transcending process through which entities (tangible and intangible elements, people, things, organizations) transcend the old into a new self, new conceptual artifacts, or structures by acquiring new knowledge in consequent knowledge-creation cycles (NONAKA; TOYAMA, 2015). For integrating human actors, proper interfaces must be developed based on the kind of data to be exchanged between the human and the system (SAHINEL *et al.*, 2019). In IoE applications data are sensed from physical sensors, virtual sensors, and social computing or participatory sensing and mobile crowd-sensing, where people collect and share sensed data (BAMGBOYE; LIU; CRUICKSHANK, 2018).

Research efforts in knowledge management propose KM frameworks to support knowledge management processes (AL-QURISHI *et al.*, 2015; MOSCOSO-ZEA *et al.*, 2019; PHILIP, 2018; PRAT, 2011; PUTRI; HUDIARTO; ARGOGALIH, 2017), but for IoE dynamics, there are minimal initiatives. The urgency for a knowledge management approach in the IoE applications also arises because tools and technologies involved and adopted should be evolved and refined (BALCO; DRAHOOVÁ, 2016), potentializing meaningful P2M and M2M collaboration (ABEBE *et al.*, 2017). In this sense, as a contribution of this thesis, Section 3.5 will present an IoE Integrated Knowledge Management Model to support intelligent services in IoE.

2.4 IoE Governance

Value-generating activities create actionable intelligence through knowledge processes that filter data, information, and knowledge (JENNEX, 2017a). A knowledge-based strategy for selecting and managing IoE enablers (things, people, data, technological capabilities, knowledge, and intelligence) assists in the governance of IoE solutions adoption. It ensures excellent benefit from IoE's capacity to provide enhanced intelligent services for the connected society. The governance of knowledge sharing in M2H interactions requires a complete taxonomy that leverages awareness from the length and breadth of the knowledge hierarchy, considering knowledge interaction and transformations from raw data to intelligence that provide outcomes and wisdom (FARIAS DA COSTA; OLIVEIRA; DE SOUZA, 2021).

Pitt *et al.* (PITT; OBER; DIACONESCU, 2017) proposed a three-layer architecture for self-governing socio-technical systems (SG-STS). These applications distinguish the interaction and co-dependence between people and information technologies in the digital transformation era. The system must be sufficiently unrestricted (resilient, flexible), to enable a shared set of congruent values to achieve the joint purpose(s) in collective actions (Figure 9).

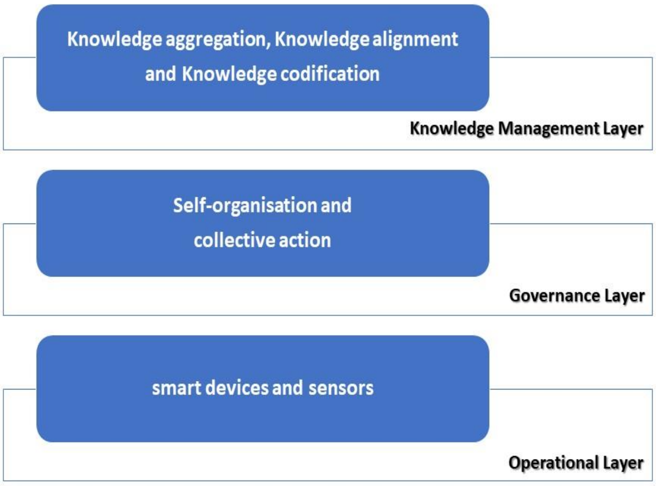


Figure 9. Three-layer architecture for SG-STS, adapted from Pitt and Ober, 2017

Many digital initiatives to modernize the public sector by connecting and integrating the physical and digital world in public or private environments are under the e-governance umbrella. However, most did not reach their full potential (SCHEDLER; GUENDUEZ; FRISCHKNECHT, 2019). In IoE disruptions, there is no centralized control and, when it comes to rules, their application, selection, and modification are performed by the participants. Accordingly, these systems need to be regulated by a type of governance based on the codification of conventional rules which should be respected and be aligned with implicit shared values (PITT; OBER; DIACONESCU, 2017).

Expecting outcomes and derived wisdom from IoE applications demand awareness considerations of IoE enablers and a proper understanding of how they contribute to knowledge transformations from raw data to intelligence (MIRAZ *et al.*, 2015) that provides outcomes and wisdom (FARIAS DA COSTA; OLIVEIRA; DE SOUZA, 2021). Awareness is commonsense knowledge about the state of a particular context (GUTWIN; GREENBERG, 2004).

For Vu (VU *et al.*, 2018), a web-based knowledge management system supports taxonomy management and evolution by matching information to existing categories so that humans and machines can organize, manage, access, and re-use information and knowledge resources more efficiently and effectively.

At the IoE landscape, some interactions and arrangements of resources can be more effective than others for value co-creation (KOMPELLA, 2020). Service innovation requires an evolving degree of reconfiguration of roles and responsibilities acceptance (MAGLIO *et al.*, 2019), materialized as governance directives and rules to guide governance by design in IoE applications.

Accordingly, taxonomies allow classifying the main concepts in a hierarchical structure and their inheritance in a graphical representation (OURIQUES *et al.*, 2019). The proposed IoE Knowledge-Based Taxonomy presented in this thesis will guide the identification of critical knowledge in IoE applications providing an in-depth classification of IoE enablers (sensors and actuators). This thesis stress that the challenge consists in the identification of critical knowledge sources in IoE solutions: how these sources collaborate and interact considering environment constraints and capabilities (technological requirements), as these interactions lead to actionable intelligence and expected outcomes in IoE solutions.

2.5 Autonomic Computing in IoE

Autonomic computing is a concept that “brings together many fields of computing to create systems that self-manage” (LALANDA; MCCANN; DIACONESCU, 2013), and their principles can be adapted to help organizations survive in high dynamic scenarios (NETO, 2012).

Ashraf et al (ASHRAF; HABAEBI, 2015) define an autonomic system as “an intelligent system, or system of systems where data acquired by sensing or monitoring capability is utilized in an overall autonomic decision-making process”.

Autonomic computing can offer new ideas to business process automation (TERRES *et al.*, 2008). Its principles can be adapted to help organizations survive in the high dynamics scenarios that call for new approaches to process management and always developing an improved strategic position (MONTEIRO JR *et al.*, 2008).

Autonomic concepts have been applied in diverse technological areas for self-management (BABAOGLU *et al.*, 2005). The philosophy of Self-$*$ (self-start) self-$*$ seeks to describe essential qualities that should constitute the behavior of an autonomic element.

Therefore, in the hyper-connected context of IoE, as in a collaborative workspace (GUTWIN; GREENBERG, 2004), humans might maintain situation awareness, to realize what are things doing in a smart environment and how things interact, can aid or be supported by people. For Gutwin and Greenberg (GUTWIN; GREENBERG, 2004), workspace awareness concerns understanding how people interact within a shared workspace. As a disruptive shift beyond the workspace to a interconnect world, IoE is envisioned to facilitate rich interactions among heterogeneous entities, ranging from devices to human actors (SAHINEL *et al.*, 2019). Service ecosystems in IoE are when the flow between actors (people and things), which integrates their competencies and resources with those of the others, results in mutual value creation (LANGLEY *et al.*, 2020).

Limiting the discussion to smart sensors in IoE, the autonomic paradigm allows for the concepts of self-learning and self-governing to exist in specific IoE domains:

An architectural framework was proposed by Kephart and Chess (KEPHART; CHESS, 2003) to make system management easier under the vision of autonomic computing. Following this, autonomic computing was re-defined as “a vision that enables any computing system to deliver much more automation than the sum of its individually self-managed parts” (KOEHLER *et al.*, 2003).

Another goal for any autonomic system is to modularly divide roles among the constituent components without sacrificing functionality. The presence of a central authority is an imperative prerequisite and allows for controlled management of the agents involved (ASHRAF; HABAEBI, 2015). It demands a new approach for IoE systems. The level of autonomy of an IoE sensor is its ability to act independently, with or without direct human intervention (ALKHABBAS; SPALAZZESE; DAVIDSSON, 2019; BERGER; DENNER; RÖGLINGER, 2018; BOYES *et al.*, 2018).

- **Ability to Self-learn**: IoT nodes equipped with smart sensors can immediately extract meaningful knowledge from the data through machine learning technologies (CHEN *et al.*, 2020) (DJENOURI *et al.*, 2021). Deep learning (DL) (AHMED *et al.*, 2020) is constantly contributing significant progress in ubiquitous smart sensing due to its dramatic superiority over traditional machine learning, the promising prospect of a wide range of applications under various contexts (REDDY; MAMATHA; REDDY, 2018).

But performing DL on mobile or embedded platforms is becoming a common requirement but it is a challenge to bridge the gap between deep learning and resource-limited platforms. In this sense, Chen and Khan (CHEN *et al.*, 2020) investigated three types of solutions: algorithmic design, computational optimization, and hardware revolution.

Alonso *et al.* (ALONSO *et al.*, 2020b) presented a novel "smarter" sensor that offers the ability to self-adjust sensing parameters update and its tuning settings during operation in real-time, in coordination with smart sensors spread across the network.

• **Ability to Self-govern**: Smart sensors are those that can communicate over a network and thus have the ability to self-identify individual networks and communication allowing reprogramming the intelligent sensor system as needed (URBINA *et al.*, 2019). Corchado *et al.* (CORCHADO *et al.*, 2021) proposed an efficient cyber-physical platform for smart management of smart territories. The solution is defined as efficient and smart because it incorporates a complete artificial intelligence suite for data analysis, data classification, clustering, forecasting, optimization, visualization, and so on. Additionally, its architecture and functionalities are also compatible with the edge computing concept, allowing for the distribution of intelligence and the use of intelligent sensors. The global intelligence of the platform could potentially coordinate its decision-making processes. Intelligent nodes are installed in the edge, by optimizing the decisions taken by human sensors through explainable artificial intelligence and data from IoT smart sensors. The proposed platform enables the development of adapted knowledge management systems with efficient computational performance and artificial intelligence algorithms.

Security approaches in IoE have to be made self-sufficient and autonomic, with minimal manual human intervention (ASHRAF; HABAEBI, 2015). As an example, a self-moving device moves autonomously and relative to its setup/installation point, without being uninstalled (e.g., smart car); whereas a non-self-moving device does not move autonomously, but can still move relative to its original location without being uninstalled (MOUNTROUIDOU; BILLINGS; MEJIA-RICART, 2019; MOUSTAKA; VAKALI; ANTHOPOULOS, 2018).

According to Kephart and Chess (KEPHART; CHESS, 2003), autonomic computing is implemented using the MAPE control loop (GANEK, 2007) which is like a structural arrangement divided into four separate parts based on their functionality, as follows:

- Monitor: Monitor module is responsible for collecting the data obtained from the environment and the data related to the element itself. This module is also responsible for the aggregation, filtration, management, and reporting of all details.
- Analyze: Analyze module provides mechanisms that model complex situations based on the received details. This allows the central authority element to learn about the environment. This module can also be used to predict future states.
- Plan: Plan module provides mechanisms that guide action with the help of higher-level policies, rules, and regulations. This module plans further action based on the constraints that have been imposed in the system. The action is performed to achieve system goals and objectives.
- Execute: Execute module controls the implementation of the devised "plan" with support for feedback.

Figure 10 presents an IoE approach of the Autonomic Control loop adapted to the IoE context. In IoE autonomic resources the challenge is to promote and improve self-learning (in Monitor and Analyze processes) and deal with self-governing when it is a necessary touch of control and governance (in Plan and Execute processes).

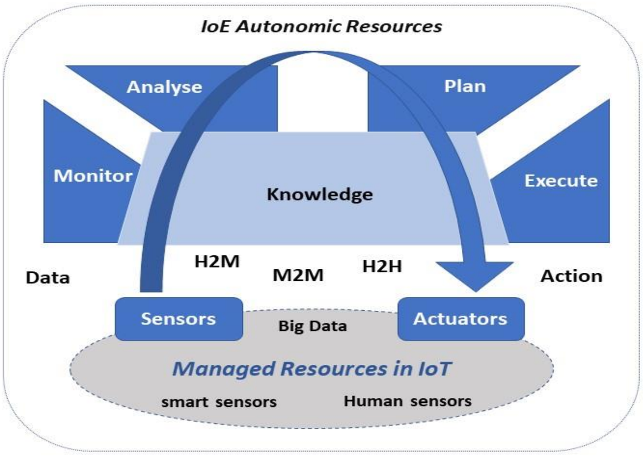


Figure 10. Autonomic Control Loop, adapted from Ganek (2007)

To integrate sensors and actuators, working together to provide various services on-demand within the IoT environment, Kang *et al.* (KANG; KIM; CHOO, 2017) proposed a self-configurable gateway featuring real-time detection and configuration of smart things over the wireless networks.

As an evolution of conventional sense-and-transmit operations in IoE applications, Yin *et al.* (YIN; WANG; JHA, 2018) proposed a hierarchical inference model for IoT applications based on hierarchical learning and local inferences. For Teng *et al.* (TENG *et al.*, 2019) the "*intelligence is derived from data*" and relates to how this data is significant in the decision-making system and segregated for future analysis purposes.

So, learning techniques are used to learn from these data to make things more intelligent. Silva *et al.* (SILVA; SAMPAIO; SOUZA, 2008) applied autonomic computing to create a framework that can self-organize based on data-embedded meta-information. Smart sensors generate smart data (which means filter out the noise and hold the valuable data). Emerging smart sensors can transmit only inference outcomes and possibly some raw data associated with rare events. So smart sensors have already performed a local inference. And edge or server inference models trained with conventional machine learning approaches should accept smart sensors inferences. The data collected from IoT data sources need to be controlled even more due to the limited capacity of these sources to ensure the security and the quality of their data (AHMED *et al.*, 2021).

Zhang *et al.* (ZHANG *et al.*, 2021) used a novel prediction machine via a self-learning generative adversarial network for soft computing applications. The system collects data through a series of high-precision IoT sensor devices and makes preliminary preprocessing. Further, the system solves the crowd prediction problem based on deep learning algorithms and obtains a reliable and accurate prediction result by continuously optimizing internal parameters.

So, the autonomic computing in IoE may benefit from a KM strategy to improve self-learning and to deal with self-governing to guarantee a touch of control of smart devices.

2.6 Service Science in IoE

Service design requires the allocation of decision control to guide and organize the service's activities (MORELLI; DE GÖTZEN; SIMEONE, 2021). Decision allocations should satisfy the consumer's sense of control without being overwhelmed by the service provider (DASU; BRUNNER-SPERDIN, 2019). Meanwhile, IoE systems' users in the digital society demands some (potentially unrestricted) self-governance (PITT; OBER; DIACONESCU, 2017). El-Sheikh *et al.* (EL-SHEIKH; ZIMMERMANN; JAIN, 2016) define digitized services as software-intensive, malleable, and usually service-oriented services. Intelligent services in IoE support value co-creation for providers and consumers, increase ecosystem capabilities and offer disruptive new business solutions with potential innovative connected functionalities.

Recently, service science has emphasized a human-centered approach, requiring the integration of multidisciplinary efforts while forwarding the dynamic reconfiguration of entities for value co-creation (SANGIORGI *et al.*, 2019). Sensing from things and people and data analytics contributes to the effectiveness and efficiency of interactions within the IoE service system. Data analytics is core to smart service systems due to continuous monitoring and learning from data (LIM; MAGLIO, 2019)(OCHS; RIEMANN, 2016). Services are constantly adjusting to nurture the evolving dynamics of service evolution and knowledge creation (SANGIORGI *et al.*, 2019).

Internet is changing ways of collecting, organizing, and disseminating information and knowledge. Knowledge creation in IoE is a challenge due to heterogeneity and unstructured data sources, large volumes of data that grow continuously (ABEBE *et al.*, 2017). Moreover, this "everything as a service" includes Knowledge as a Service (KaaS), providing critical knowledge as a product, and Knowledge Management as a Service (KMaaS), providing knowledge management services to the consumers (BALCO; DRAHOOVÁ, 2016)(AL-QURISHI *et al.*, 2015).

Nowadays, exchanging services, robust connectivity, dynamic changes, and service values are central in society. IoE is the paradigm of intelligent services. The central core in IoE is the "intelligent connections" and information derived from data that creates 'value' and insights. Accordingly, intelligent, or smart services have tangible and intangible elements for value creation and outcomes.

Dreyer *et al.* (DREYER *et al.*, 2019) argue that the intelligence of connected systems and devices is in constant evolution and adaptation through collaboration. The authors define smart services as individual, highly dynamic, and quality-based service solutions convenient for the consumers. So, it is imperious to be ready for the digitalization era and disruptive innovations, from simple changes to complex disruptions, originated from technological and non-technological trends.

Therefore, in the digitalization era, the value creation process implies negotiation among different actors and may require facilitation in the form of interaction mechanisms between service providers and consumers. In many cases, consumers are dynamically transformed into co-producers (MORELLI; DE GÖTZEN; SIMEONE, 2021).

Morelli *et al.* (MORELLI; DE GÖTZEN; SIMEONE, 2021) analyzed the interaction among enablers (producers and consumers) in a service system that defines the roles and knowledge that contribute to shaping services as a value creation process. These enablers' interactions define three interpretations centered around the process of value creation:

1. ***Services as Interactions***: Consists in interactions in time and context between two or more entities characterized by unbalanced roles between the provider(s)

and consumer(s) for value co-creation. For intelligent services in IoE, the interactions are machine to machine (M2M), human to machine (H2M), and human to human (H2H).

2. ***Services as Infrastructure***: Consists in infrastructure for value co-creation – physical, functional, or organizational infrastructure which operationalizes interactions and supports service activities. The IoE environment relates to IoT, the intelligent network infrastructure, big data analytics, and IoE applications.

3. ***Services as a Systemic Institution***: Consists in the institutional system or aligning services to the institutional context (governance). Represents the social, technical, and regulatory context to institutionalize and organize value creation activities and processes. In the IoE context, it represents the value and innovation attitudes of a connected society.

These three interpretations, when taken together, define possible contexts for service design and define an IoE ecosystem supported by intelligent service orientation, which is essential for digital transformation (digitalization) (MORELLI; DE GÖTZEN; SIMEONE, 2021). Figure 11 shows how IoE is built upon the "four pillars" of people, data, processes, and things connected by intelligent services in the network.

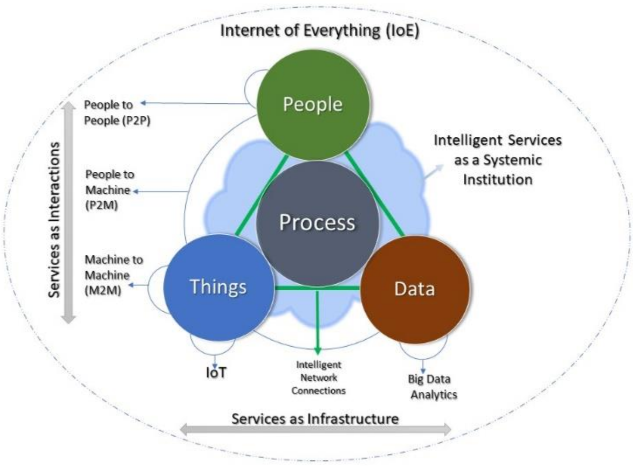


Figure 11. Service Interactions in IoE (elaborated by the author)

Service ecosystems in IoE are when the flow between entities (people and things) integrates individuals' competencies and resources with those of the others, resulting in mutual co-created value. It serves as a new context of services in a many-to-many, interconnected world, empowered by a continual and evolving flow of intelligent connections. And when the moments of insights and foresight in IoE result in a ***valuable and unanticipated*** outcome, the *Serendipity* phenomenon (OCED, 2021) occurs beneficially. The next section studies the relationship between Serendipity and IoE and investigates the benefits of serendipity by design in IoE applications.

2.7 Serendipity in IoE

Serendipity definition is "*the occurrence and development of events by chance in a happy or beneficial way"* (OCED, 2021). The term is originated from the fairytale "The Three Princes of Serendip". In the story, the princes "*were always making discoveries, by accident and sagacity, of things they were not in quest of*".

Serendipity occurs in unexpected circumstances when a moment of insight results in a valuable, unanticipated outcome. Although the occurrence of serendipitous events cannot be directly controlled, they can be potentially positively influenced and supported by effective digital information environments (MAKRI *et al.*, 2014).

For Makri *et al.* (MAKRI *et al.*, 2014), designing technology to support serendipity is twofold: the more one attempts to "engineer" serendipity through technology, the fewer users may perceive the experience to be serendipitous. Some components of serendipity are novelty, diversity, and unexpectedness. Kamienski *et al.* (KAMIENSKI *et al.*, 2018) emphasize the need for context-aware systems able to adapt behavior automatically to instant environment conditions. Currently, there is a gap in terms of understanding how context information is interrelated, as well as tracking visualizing, specifying, and monitoring typical contexts involved in IoE-based applications.

For McCay-Peet *et al.* (MCCAY-PEET; TOMS; KELLOWAY, 2015) serendipity is "*an unexpected experience prompted by an individual's valuable interaction with ideas, information, objects, or phenomena*". The authors studied under what conditions is serendipity most likely to occur and to what extent it is influenced by its actor's interaction processes or by the environment or context in which they are immersed. They conclude that some types of digital environments, (e.g., websites, databases, search engines, intranets, social media sites) may be more conducive to serendipity than others.

Human characteristics may influence the ability to experience serendipity, such as extraversion. Exogenous influencers are perceptions of the context in which people are immersed, including a trigger-rich creative environment that enables connections, and leads to the unexpected. The environment in which the user is immersed may create a fertile environment for serendipity to occur. This definition is in line with the IoE concept.

In the perspective of McCay-Peet & Toms (MCCAY-PEET; TOMS, 2018), to operationalize and recognize a serendipitous phenomenon, it might support five conditions: (1) the observation is unexpected and unpredictable; (2) knowledge to identify the observation; (3) space and time to absorb it, recognize its value, and the perseverance to act on it; (4) follow-up time to explore the observation; and (5) and a valuable outcome.

In resume: *"for an event, outcome or process to be serendipitous, it is initiated with an anomalous observation by a person who has the requisite skills to observe its irregularity, and the mental space to follow through on the observation, taking whatever requisite time is required to turn it into an unexpected finding"* (MCCAY-PEET; TOMS, 2018).

Related to digital environments, serendipity is mainly approached as either quality of an event or a process or experience, which has one or more serendipitous qualities and characterizes the successful outcome of a task (MCCAY-PEET; TOMS, 2018).

Serendipity is not particularly susceptible to systematic control and prediction. However, it may also have a role in revealing hidden connections or "hidden analogies", revealing creative connections through serendipitous links between information sources (FOSTER; FORD, 2003). It is an interesting phenomenon to study in information science. Understanding connections when designing physical and digital environments interactions can facilitate serendipity. Serendipity is defined as what happens in unplanned ways when resources (information, things, people, etc.) correspond with each other.

This thesis proposes a definition for Serendipity in IoE environments, extending (MCCAY-PEET; TOMS, 2018) definition:

> *"In **IoE** context, for an event, outcome, or process to be serendipitous, it is initiated with an anomalous observation by a sensor node **(people or machine)**, which has the requisite **intelligence** to observe its unexpected finding, and the **cyber-physical space and technological capabilities** to follow through on the observation, taking whatever requisite of **time and reach** is required to turn it into **valuable outcomes**".*

Björneborn et al (BJÖRNEBORN, 2017) presented a framework that introduces three key affordances for facilitating serendipity: ***diversifiability***, ***traversability***, and ***sensoriability***, covering capacities of physical and digital environments to be diversified, traversed, and sensed. The framework is structured around couplings between the three key affordances and three key personal serendipity factors: ***curiosity (self-learning)***, ***mobility***, and ***sensitivity (monitoring)***. The authors affirm that it is impossible to "*engineer*" or "*design*" serendipity, but it is important to design affordances for serendipity. And concludes that serendipity may thus be intended by designers but must always be unplanned by users.

Table 2 presents the framework proposed by Björneborn et al (BJÖRNEBORN, 2017). The conceptual framework presents ten "serendipity dimensions" grouped into three key affordances: diversifiability, traversability, and sensoriability. The affordances deal with how physical and digital environments can be diversified, traversed, and sensed, thus covering key aspects of human interactions with environments.

In the framework, serendipity is seen as a possible outcome when personal factors of curiosity, mobility, and sensitivity correspond with affordances of diversifiability, traversability, and sensoriability in a given environment. However, even it is not possible to "design serendipity," it is possible to design for serendipity. It is important to design affordances for serendipity – seen from the designers' point of view. From the people's point of view, serendipity must always be encountered in unplanned ways to be serendipitous.

Table 2 presents key affordances and sub-affordances for serendipity with coupled personal factors and sub-factors.

Table 2. Conceptual Framework for Serendipity, adapted from Björneborn (2017)

10 Sub-affordances for serendipity	3 Key affordances for serendipity	3 Key personal factors for serendipity	10 Personal sub-factors for serendipity
Diversity (multiple potentials) Cross-contacts (colliding potentials) Incompleteness (finalizable potentials)	**Diversifiability**	**Curiosity**	Interest (regarding diversity, etc.) Playfulness (regarding cross-contacts, etc.) Inclusiveness (regarding incompleteness, etc.)
Accessibility (access to specific spot, convergently) Multi-reachability (reaching anywhere, immersively) Explorability (inviting somewhere else, divergently) Slowability (affording slower pace, frictionally)	**Traversability**	**Mobility**	Searching (convergent) Immersion (both convergent and divergent) Exploring (divergent) Stumbling (both divergent and convergent)
Exposure (highlighting broader, over longer time) Contrasts (highlighting sharper, more suddenly) Pointers (highlighting narrower, more specifically)	**Sensoriability**	**Sensitivity**	Attention (broader sensing) Surprise (unprepared sensing) Experience (prepared sensing)

Specifically, to support and design affordances for serendipity in the IoE environment – *diversifiability* of information sources, *traversability* in the immersive physical-digital environment, and *sensoriability* of data are the major research challenge. Related to machines' point of view, serendipity may be related to self-learning and self-governing to identify opportunities for knowledge creation through M2M and H2M interactions.

Intelligent environments will be created with communication and services seamlessly adapted to the pervasive IoE contexts, where customized interconnectivity is provisioned to enable specific applications at the individual device and infrastructure levels (YOUNIS, 2018).

2.8 IoE Interoperability

Interoperability needs to be resolved to allow interaction between devices and users located within and across different smart spaces. Some technical issues that must be taken into consideration in designing smart spaces are changing the focus from a technology-centric to a user-centric approach, emphasizing the user's understanding of the system's behavior and functions of devices and the balance between user-device control (ALAVI *et al.*, 2018).

IoE sensors' ability to communicate and share information and knowledge may vary at different levels of interoperability. Noura *et al.* (NOURA; ATIQUZZAMAN; GAEDKE, 2019) classified interoperability in the following levels: no connection (no interoperability between IoE enablers), technical (basic connectivity and network connectivity), syntactical (data exchange interoperability), semantic (understanding in the meaning of the data), pragmatic/dynamic (applicability of the information), or conceptual (shared view of the world) (NOURA; ATIQUZZAMAN; GAEDKE, 2019).

Taxonomies work more in the sense of organizing information and/or knowledge in hierarchical relations between the terms. Ontologies, on the other hand, try to establish semantic relations between concepts (VITAL; CAFÉ, 2011), providing semantic interoperability (BARNAGHI *et al.*, 2012). To support interoperability between different semantic descriptions in the IoE domain, the ontologies and semantic models need to be simple and lightweight to make them suitable for resource-constrained environments (BARNAGHI *et al.*, 2012).

Semantic descriptions can support and interoperability between different sources (BARNAGHI *et al.*, 2012). Several approaches and semantic web techniques for better representation and exploration of the data were proposed to extract knowledge from data and to successfully understand and extract value from this data (RISTOSKI; PAULHEIM, 2016). Much sensor data is now being annotated with a sensor ontology (i.e., SSN ontology), encoded in standard Web formats (i.e., RDF), and is increasingly being made available on the Web (i.e., as Linked Data) (BARNAGHI *et al.*, 2012). The human data model proposed by (SAHINEL *et al.*, 2019) is used to define human agents that represents human actors in the cyber world.

The W3C Semantic Sensor Networks Incubator Group (the SSN-XG) has developed an ontology for describing sensors and sensor network resources, called SSN (BARNAGHI *et al.*, 2012). In the existing IoT ontologies, it serves as a top-level ontology or foundation ontology to be extended and instantiated by subsequent IoT ontologies (RISTOSKI; PAULHEIM, 2016). The ontology provides a high-level schema to describe sensor devices, their operation and management, observation, and measurement data (YOU; LI; CHEN, 2018). Sensor or sensor-related ontologies can describe sensors in terms of sensor capabilities, measurement processes, observations, and deployments. Langley *et al.* (LANGLEY *et al.*, 2020) presented a taxonomy of smart things in IoE context limited on capabilities, connectivity, and levels of smartness of things.

Many studies have focused on the interaction among sensors and actuators in tri-space (cyber, physical, and cyber-physical). Kotis and Katasonov (KOTIS; KATASONOV, 2013) presented a framework for supporting semantic interoperability between many distributed and heterogeneous IoT entities (sensors, actuators, and applications). Farias da Costa *et al.* (COSTA; OLIVEIRA; SOUZA, 2021) developed an observatory specifically for cataloging IoE enablers (sensors and actuators) and to support sensors and actuators selection in IoE applications and highlight often overlooked details regarding proper intelligent management issues.

IoE ecosystem is characterized by a high degree of heterogeneity, and it exists to enable many entities to pool their resources to connect and interact with heterogeneous sensors, actuators, and controllers, making them interoperable to create significant opportunities for new applications and services. Fortino *et al.* (FORTINO *et al.*, 2018) presented INTER-IoT, a bottom-up approach to support IoT stakeholders in the design of open IoT devices, smart objects, services, and complex systems, thus creating new IoT interoperable ecosystems. Le-Puhoc and Hauswirth (LE-PHUOC; HAUSWIRTH, 2018) address the interoperability issue of IoE by laying out the extended version of linked data principles for publishing and consuming data into a hypergraph which is made programmable agnostic to networking technologies and platforms.

Song *et al.* (SONG *et al.*, 2021) propose a methodology for modeling interoperability of smart sensors in terms of interactions using labeled transition systems and finite-state processes to quantitatively and automatically measure and assess, identify and resolve interoperability issues, and improve interoperability.

Smart devices equipped with artificial intelligence (AI) provide the deployment of innovative IoE-based applications, where people (as human sensors) and things (sensors and actuators) interact appropriately within a social context and multi-user environment (MIRAZ; ALI; EXCELL, 2015).

For Sehrawat and Gill (SEHRAWAT; GILL, 2019), sensors play an important role in the automation of any function, measuring and processing the collected data to detect changes in physical things. However, there are different types of sensors that can range from very simple to very complex as the task of sensing has been aided by various technologies and the increasing inclusion of computational capabilities.

To support the digital transformation in Industry 4.0, Colly *et al.* (COLLI *et al.*, 2019) presented an assessment approach to provide, as an outcome, an assessment of the current maturity stage of a company towards its evolution path concerning the digital transformation of the industrial sector. It considers the preparedness for the enabling of data ubiquity and connectivity capabilities. However, the authors perceived the need for context-specific general improvement recommendations and neglected a knowledge management approach regarding knowledge flows of smart sensors in H2M, H2H, and M2M interactions. The IoE Integrated Knowledge Management Model will support maturity stages progression towards IoE interoperability (presented in Chapter 3).

This thesis contributes to the development of a taxonomy related to IoE applications, which will guide interested researchers in this field and also application developers in designing IoE knowledge-intensive services. Considering that awareness of actions and intentions is the understanding of what another entity is doing, either in detail or at a general level (GUTWIN; GREENBERG, 2004). Actions and interactions with the environment create and enlarge knowledge through the conversion process of tacit and explicit knowledge (NONAKA; TOYAMA, 2015).

This Chapter aimed to contribute to a better understanding of interactions among people and things in the IoE context, considering a knowledge management perspective. In Chapter 3, in a knowledge-based approach to support KM in IoE applications, the IoE Knowledge-based taxonomy will be presented to support awareness of IoE enablers, an IoE Integrated Knowledge Management Model (IoE IKM Model) is proposed to guide KM strategy in IoE context and requirements to evaluate smart sensors will support the design of IoE solutions. The use of a platform such as the IoE Database, presented in Section 3.6, is a central repository for the IoE body of knowledge.

3 Proposition: A Knowledge-based approach

This Chapter conducts a literature review about IoE and IoT taxonomies and, from this, the IoE Knowledge-based Taxonomy is presented. In Section 3.3, the proposed taxonomy is evaluated. An IoE Integrated Knowledge Management Model (IoE IKM Model) is presented to support knowledge strategy in IoE applications design and utilization. Smart Sensors requirements are defined in Section 3.5. Finally, the IoE Database is presented. It is a platform to support the IoE body of knowledge and the evolution of the IoE Knowledge-based taxonomy.

3.1 IoE Taxonomies: A literature review

Taxonomies represent sense-making structures (EDWARDS, 2015) (p.51) for organizing information and knowledge into hierarchical relationships between the terms. This involves studying how the theories evolve, which enables researchers to study the essences and their relationships in the research territory (NICKERSON; VARSHNEY; MUNTERMANN, 2013).

As a form of classification (NICKERSON; VARSHNEY; MUNTERMANN, 2013), a taxonomy for IoE sensors and actuators that considers knowledge enablers will support the understanding of sensor types, how they are combined and used in different application domains, and how issues with capabilities and observations can affect the quality of services and knowledge creation. To develop a taxonomy for IoE sensors, existing taxonomies were reviewed related to IoT and IoE. The first step in developing our taxonomy was to review the existing classification schemes, semantic descriptions, and taxonomies, which could suggest design implications for IoE systems.

The methodological guidelines suggested by Kitchenham and Charters (KITCHENHAM *et al.*, 2010) for literature reviews guided this survey. The review included contributions from the ACM Digital Library, IEEE Digital Library, ISI Web of Science, Science@Direct, and Scopus databases, which were the most relevant for finding specific studies in journal and conference papers in English. The following specific search string was sought: ("internet of everything" OR "IoE" OR "internet of things" OR "IoT") AND ("taxonomy") in the "Title", "Abstract", or "Keywords" fields.

The designed search string retrieved from the databases as many studies as possible that were relevant to the review, even if the query results returned articles not relevant to the survey. Relevant studies not retrieved after the first query were also included in a second iteration analysis in June 2020, considering studies likely to be explicitly related to IoE. Furthermore, most contributions were survey papers for IoT, which indicates a lack of maturity in work in the field of IoE.

Only studies published in English in journals (already published and in press), conference proceedings, books, and technical reports were selected. After discarding the duplicates, a total of 394 candidate articles remained from the initial search (Table 3).

Table 3. Summary of literature review stages.

Literature review stage	number of papers
Search of ISI Web of Science	235
Search of Scopus	323
Search of IEEE	118
Search of ACM Digital Library	22
Science@Direct	62
Total	**760**
Duplicates	366
Total after discarding duplicates	394
Approval for analytical reading	**76**
Discarded	318

Each candidate article was subjected to the following before its eventual selection: 1) evaluate the title and read the summary, and then delete the article if not related to IoE or IoT taxonomies; 2) retrieve the paper and read the introduction and conclusions; and 3) critically assess the quality of the contribution and discard it if not related to the research aim. The quality parameters considered were the study's degree of adherence to IoE applications and the contribution's relevance.

Finally, after applying the filters, 76 articles relevant to this literature review remained. The studies were diverse and promoted different approaches. From the list of papers selected, it was possible to extract works related to IoT and IoE taxonomies, thus revealing the proposed IoE taxonomy. A qualitative analysis of the results provided some guidelines and a comprehensive overview of the topic that supported the novel IoE taxonomy proposal.

3.2 The proposed IoE Knowledge-based Taxonomy

This section will present the proposed IoE Knowledge-based taxonomy published in January 2021 in MDPI Sensors Journal (https://www.mdpi.com/1424-8220/21/2/568/htm). For the development of this taxonomy, an iterative approach was followed, as suggested by Nickerson *et al.* (NICKERSON; VARSHNEY; MUNTERMANN, 2013). The taxonomy identifies and categorizes sensors, attributes, and characteristics that are important for developing IoE applications for distinct domains. This proposed taxonomy is the first attempt to address knowledge classification and how knowledge processes lead to intelligent services in IoE applications.

The development of an IoE taxonomy involves specifying the characteristics of the sensors and actuators in IoE applications that arise from a refinement process at various stages, to sufficiently fulfill the following qualitative attributes from (NICKERSON; VARSHNEY; MUNTERMANN, 2013), regarding the taxonomy:

- Concise: It has a limited number of dimensions and limited characteristics and is restricted to what is relevant and understandable.
- Robust: It contains enough dimensions and characteristics to represent the objects of interest.
- Comprehensive: It includes the main dimensions and characteristics of the objects of interest and can classify all known objects within the considered domain.
- Extendable: It allows for the inclusion of new dimensions and additional characteristics within a size when new demands appear.
- Explanatory: It provides useful explanations and valuable descriptions of the nature of the objects under consideration.

The taxonomy's purpose (meta-characteristic) drives the taxonomy's dimensions and characteristics (NICKERSON; VARSHNEY; MUNTERMANN, 2013). Each element or classification proposed in the taxonomy should be a logical consequence of its meta-characteristic. The proposed taxonomy aims "to classify sensors in IoE applications (human and non-human based) based on the knowledge they provide in intelligent tasks".

To elicit main characteristics in IoE applications and to understand the IoE domain, specific questions were applied by answering the 4 Ws (What, When, Who, and Where) and 1 H (How) identified using the 4W1H methodology (BAJAJ *et al.*, 2018). This development methodology addresses the challenge imposed due to the high heterogeneity of existing IoE devices. A similar approach was proposed in (BISDIKIAN; KAPLAN; SRIVASTAVA, 2013) to measure the quality and value of information when considering the benefits and value created by IoE applications. From these questions, it was able to define the following four complementary categories that drive the purpose of taxonomy dimensions and characteristics:

- Knowledge: Refers to knowledge in action; that is, the artifact or information within a context (*what*) with understanding and meaning.
- Type: Represents sensors and actuators characteristics — *who* they are, their physical characteristics, their usage, and their role in IoE context: sensors or actuators in cyber, physical, or cyber-physical presentation.
- Observation: Refers to the physical context in time (*when*) and space (*where*); that is, the location and time related to monitoring the sensed data within ever-changing IoE contexts.
- Capabilities: Relates to *how* the information is delivered, the infrastructure capabilities, and the resources required.

Then in the top-down development process, the first step started with defining the most general categories (*Knowledge*, *Type*, *Observation*, and *Capabilities*), and after that determining dimensions and characteristics of the sensors in the IoE taxonomy.

The taxonomy dimensions and characteristics were derived from a theoretical foundation from reviewing the related literature, as presented in Section 3.1. The proposed IoE taxonomy consists of four categories (see Figure 12), and groups 18 dimensions, each consisting of mutually exclusive and collectively exhaustive characteristics. Section 3.2.1 describes the *Knowledge* category, which analyses the knowledge characteristics and the value created by IoE applications. Section 3.2.2 details sensors characteristics related to their use in IoE applications (*Types*). Section 3.2.3 presents the *Observation* category, which classifies how data are sensed and gathered in IoE observations. Finally, in Section 3.2.4, the sensors' *Capabilities* are classified into a few dimensions that address the technological aspects for designing IoE applications.

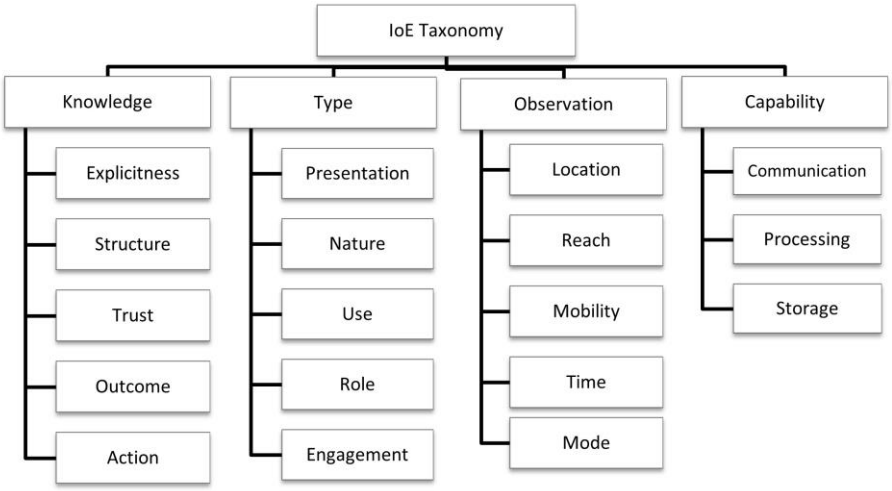


Figure 12. IoE Knowledge-based taxonomy

3.2.1 Knowledge

The *Knowledge* category consists of five dimensions related to knowledge and information: Explicitness, Structure, Trust, Outcome, and Act.

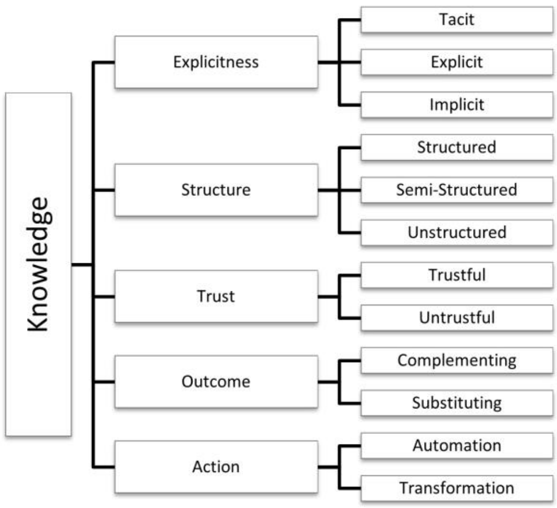


Figure 13. Knowledge Category, dimensions, and characteristics

3.2.1.1 Explicitness

Knowledge discovery approaches used in developing IoT solutions (POZZA *et al.*, 2015), which involve sharing information from smart objects, should be optimized by examining how humans process data sources of information to form knowledge (SHAHID; ANEJA, 2017). IoE environment architectures consist of IoT standard architecture (DE MATOS; AMARAL; HESSEL, 2017), but with the addition of the human element (which acts as a node) to contribute for intelligent services to the IoT network (NEZAMI; ZAMANIFAR, 2019). For Perera *et al.* (PERERA *et al.*, 2014), this requires knowledge from different perspectives; for example, knowledge of sensors, application domains, users, and activities. And these uncovered knowledge patterns are analyzed and integrated for subsequent use in real-time, using multiple knowledge management approaches (BONTE *et al.*, 2019; GE; BANGUI; BUHNOVA, 2018; UR REHMAN *et al.*, 2017). This dimension considers the addition of the human element and the intelligence of connected things ranges from nonexistent to perfectly rational (ALKHABBAS; SPALAZZESE; DAVIDSSON, 2019). There are different kinds of knowledge, and it demands distinct representations. Regarding explicitness, this dimension classifies knowledge provided by sensors in IoE applications into three distinct types:

3.2.1.1.1 Tacit

Tacit knowledge is human sensors' knowledge and is rooted in actions, experiences, and involvement in specific contexts. Tacit knowledge consists of people's knowledge based on intuitive evaluations of sensory inputs and perceptions, which is sometimes hard to express (EIN-DOR, 2011). Enhancement of human senses through sensor and data fusion and context awareness is the background that enables smarter wearable devices for interacting with human cognitive memories (PERERA; VASILAKOS, 2016).

3.2.1.1.2 Explicit

Explicit knowledge is knowledge codified and articulated (EIN-DOR, 2011). Explicit knowledge from hard sensing-based data acquisition results in discovering hidden patterns in the aggregated sensor data (CHAOCHAISIT *et al.*, 2016; OBINIKPO; KANTARCI, 2017). The explicitness refers to awareness of a fact and the application of knowledge (PERERA; VASILAKOS, 2016) from efficient scheduling of the resources (HUI; SHERRATT, 2017; MAHDAVINEJAD; REZVAN; BAREKATAIN, 2018; POZZA *et al.*, 2015).

3.2.1.1.3 Implicit

Implicit knowledge may be implicit information intertwined in information systems and data sources (EIN-DOR, 2011). It is derivable from various assumptions (GRANT; PARISI, 2010) and inferences. Thus, many data analytic algorithms can be applied to data to extract a higher level of implicit knowledge (MAHDAVINEJAD; REZVAN; BAREKATAIN, 2018). Implicit knowledge emerges from machine learning and AI technologies, mainly in machine intelligence services (HÖLLER; TSIATSIS; MULLIGAN, 2017). It consists of outputs to make predictions oriented toward decision support and automation in diverse IoE application scenarios (RUTA *et al.*, 2018).

3.2.1.2 Structure

Sensor data is a piece of explicit knowledge with meta-information (or metadata) representing the body of evidence (BISDIKIAN; KAPLAN; SRIVASTAVA, 2013). Knowledge is created by transforming the multiple data formats collected (structured, semi-structured, and unstructured) (EIN-DOR, 2011) (DAMIANI, 2015) into high-level information (PAL; VANIJJA; VARADARAJAN, 2018; PERERA *et al.*, 2014; UR REHMAN *et al.*, 2017; YEBDA *et al.*, 2019), and useful knowledge patterns (PERERA *et al.*, 2014). The combination of data streams with background knowledge enables meaningful analysis to extract higher levels of abstraction and provide quality actionable information to IoE services (BONTE *et al.*, 2019; MAHDAVINEJAD; REZVAN; BAREKATAIN, 2018; QANBARI *et al.*, 2015). Descriptions of these data formats are given below:

3.2.1.2.1 Structured

Structured data have a standard defined format and a relational structure often managed using a standard SQL-type language and stored in relational database management systems. Examples of structured data are string, numeral and date (MOHAMED *et al.*, 2019).

3.2.1.2.2 Semi-structured

Semi-structured data cannot be managed by traditional database management system techniques, but the understanding and analysis of such data require comprehensive and intelligent rules (BUGEJA; DAVIDSSON; JACOBSSON, 2018; HÖLLER; TSIATSIS; MULLIGAN, 2017; MOHAMED *et al.*, 2019).

3.2.1.2.3 Unstructured

Unstructured data do not follow any specific pre-defined format and are often represented in a rather complex structure that contains hidden relationships. Examples of unstructured data are videos, text, time information, and geographic location (MARJANI *et al.*, 2017). With the volume of data generated by sensors, devices continuously generate large amounts of structured, unstructured, and semi-structured data, which results in ”big data” (GAO; LEI; YU, 2015; YAQOOB *et al.*, 2016).

3.2.1.3 Trust

Trust management is a critical challenge for IoE/IoT platforms (ASGHARI; RAHMANI; JAVADI, 2018; JING *et al.*, 2014). In a hybrid human-based and device-based environment, data's trustworthiness can be estimated mostly by the sensor nodes' reputation (HARON *et al.*, 2017).

Trust refers to any direct or indirect interactions of users' information with sources or connected objects within IoT landscapes (JING *et al.*, 2014) (BARKER *et al.*, 2014).

Dynamic and heterogeneous network environments and the diversity of devices connected in the IoT generate a vast array of security threats (AHAD; TAHIR; YAU, 2019; ASGHARI; RAHMANI; JAVADI, 2019; HASSAN *et al.*, 2018; NOURA; ATIQUZZAMAN; GAEDKE, 2019). The network management level should handle issues such as security of the data to be transmitted (YEBDA *et al.*, 2019), and a coherent IoT architecture would provide a layer of data security (BARKER *et al.*, 2014; BOTTA *et al.*, 2016), and users' awareness about the consequences of potential IoT threats may reduce the risk of exposure (ASHRAF; HABAEBI, 2015; BISDIKIAN; KAPLAN; SRIVASTAVA, 2013; NESHENKO *et al.*, 2019; PHUTTHARAK; LOKE, 2019).

Knowledge assets vary in veracity levels (EIN-DOR, 2011), between the extremes of truth and untruth (BAMGBOYE; LIU; CRUICKSHANK, 2018). Sensor networks' applications need support regarding privacy, security accuracy, timeliness, relevance, completeness, and provenance (BISDIKIAN; KAPLAN; SRIVASTAVA, 2013; CHEN; HELAL, 2011). The data source's reputation represents the source's truthfulness in providing quality content to handle changing external requirements and contexts (HÖLLER; TSIATSIS; MULLIGAN, 2017). The trust values are considered based on the reliability of devices and the level of security and trust involved in establishing and operating the connectivity (BOYES *et al.*, 2018; SIOW; TIROPANIS; HALL, 2018a). Knowledge of sensors and sensor data in IoE application is either trustful or untrustful:

3.2.1.3.1 Trustful

Knowledge of sensors data sources is trustful when it regards establishing meaningful identity, using trusted communication paths, and protecting contextual information essential to ensure the protection of users' privacy in the IoE environment (CHELLAPPAN; SIVALINGAM, 2016). It is based on protecting both users' and service providers' privacy precedents (MARJANI *et al.*, 2017). Alsamani and Lahza (ALSAMANI; LAHZA, 2018) addressed the security of IoT objects and privacy issues by combining identification, authentication, and authorization into one concept: access control, consisting of five concepts: access control, confidentiality, integrity, availability, and non-repudiation. Other studies have covered concerns such as anonymity, liability, and moral, ethical, legal, cultural, and regional parameters, among other things (ABBAS *et al.*, 2018; BELLAVISTA; BERROCAL, 2019; FORTINO *et al.*, 2014; SHOLLA; NAAZ; CHISHTI, 2017).

3.2.1.3.2 Untrustful

Untrustful and misleading data could lead to wrong decisions and severe consequences and lead to uncertainty at all knowledge transformation levels. Incompleteness in data occurs at the lower layer of the sensor readings or raw data collected. Vagueness frequently appears at a higher level of contextual information (HARON *et al.*, 2017; SHAH *et al.*, 2019). Another security risk associated with IoT data is the heterogeneity of the devices used (ZHANG *et al.*, 2018), which further complicates access control decisions.

3.2.1.4 Outcome

Considering the type of information exchanged between humans and the system (SAHINEL *et al.*, 2019), the expected outcomes from IoE applications provide multiple tiers of cognition from heterogeneous contexts (OTEAFY; HASSANEIN, 2019). Human aspects contemplated by collaboration theory and technical aspects are challenges in computer network theory that require efficient solutions in distinct levels of collaboration between IoE resources (ERIS; DRURY; ERCOLINI, 2015). It is imperative to provide awareness of collective intelligence and where the intelligence is (BOYES *et al.*, 2018), representing the outcomes expected in designing the IoE solutions, based on the application domain (ERIS; DRURY; ERCOLINI, 2015; PAL; VANIJJA; VARADARAJAN, 2018).

The Outcome dimension refers to the degree to which knowledge sources (things and humans) contribute to knowledge value in IoE intelligent services. Relevant knowledge contributions either complement or substitute (or both in some cases) to provide benefits, and sometimes automate or transform traditional tasks (ALSAMANI; LAHZA, 2018) into IoE environment disruptions.

3.2.1.4.1 Complementing

Represents knowledge sharing between IoE sensors and actuators. An example is human mobile devices as sensors collect human observation and information about the environment and infrastructures (OBERLÄNDER *et al.*, 2018; PHUTTHARAK; LOKE, 2019; YAQOOB *et al.*, 2017).

3.2.1.4.2 Substituting

Represents a novel interpretation of reality to enhance the quality of life (livability), regarding knowledge acquisition as the "core element" and the realization of "intelligence" (MOUSTAKA; VAKALI; ANTHOPOULOS, 2018) and serendipitous outcomes.

3.2.1.5 Action

The Action dimension refers to knowledge creation and actionable intelligence to promote automated processes (OBERLÄNDER *et al.*, 2018), (BISDIKIAN;

KAPLAN; SRIVASTAVA, 2013; RUSSELL; NORVIG; DAVIS, 2016; YAQOOB *et al.*, 2017), or transforming and changing the state of their environment (ALKHABBAS; SPALAZZESE; DAVIDSSON, 2019).

The goals of IoT systems range between general and specific, and include, for example, monitoring, reducing costs, and improving utilization and goals (ASGHARI; RAHMANI; JAVADI, 2019).

For Russell *et al.* (RUSSELL; NORVIG; DAVIS, 2016), a rational agent acts to achieve the best outcome or the best-expected outcome. There is a close interrelationship between intelligence and automation (ALSAMANI; LAHZA, 2018), or creating and pursuing goals through transformation. Sensor information in IoE applications provides either automation or transformation of the IoE environment, which are defined as follows:

3.2.1.5.1 Automation

The automation of tasks and dependency on machines may reduce human abilities (MOHAMED *et al.*, 2019). When combined with AI and machine learning, IoE applications will benefit from automated decision making (ATAT *et al.*, 2018) and automated tasks, with efficient usage of network resources, minimization of operational costs, coordination of computational resources, and efficient and effective data management mechanisms (HASSAN *et al.*, 2018) all of these associated with the quality of experience (AHMED *et al.*, 2016; PAL; VANIJJA; VARADARAJAN, 2018).

3.2.1.5.2 Transformation

When an IoE solution provides transformation, smart sensors act independently, with minimal or no human intervention (OBERLÄNDER *et al.*, 2018). With the support of IoT and AI, humans benefit from improvements in technological advancements (HÖLLER; TSIATSIS; MULLIGAN, 2017; OBINIKPO; KANTARCI, 2017) by collecting, modeling, and reasoning the context (PERERA *et al.*, 2014). Raw observations can be transformed into higher-level abstractions (OTEAFY; HASSANEIN, 2019) that are meant for human or automated decision-making processes (ALSAMANI; LAHZA, 2018).

Considering how actions generate changes in the environment to achieve the desired goal(BELLAVISTA; BERROCAL, 2019; LANGLEY *et al.*, 2020), automation and transformation processes may respond and interact with the environment in assisting the evolutions of future systems, defined in (LANGLEY *et al.*, 2020), which can be:

Reactive: Consists in the ability to immediately adjust to a changing environment.

Adaptive: Consists in the longer-term ability to adjust their behavior to changes.

Predictive: Consists in the ability to use computation and analytics techniques to find in-depth knowledge of the environment, and the most appropriate solutions or possible evolutions to each IoE system situation.

3.2.2 Type

The Type category contains five dimensions for the classification of sensors and actuators: Presentation, Nature, Use, Role, and Engagement.

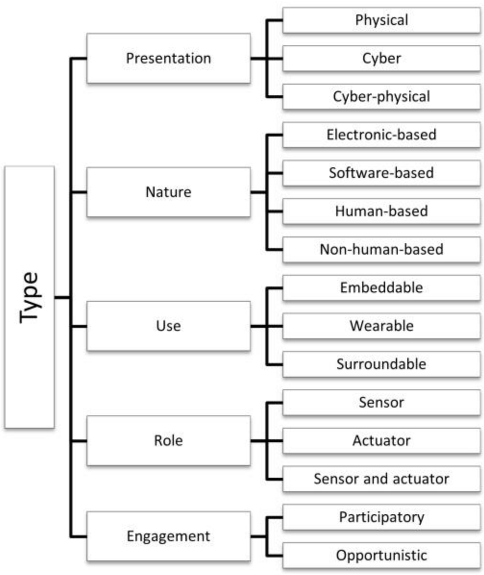


Figure 14. Type Category, its dimensions, and characteristics

3.2.2.1 Presentation

Presentation relates to the physical aspects of sensors and actuators that interact with the physical world. The physical and virtual world integrate computation and physical processes in one of the following ways: a) physical, b) cyber or virtual, and c) cyber-physical, logical or software sensors (AGARWAL *et al.*, 2016; ARMANDO *et al.*, 2018; CHEN; HELAL, 2011; SAHINEL *et al.*, 2019; SALIM; HAQUE, 2015; SINCHE *et al.*, 2019).

Human sensors collect data for the sensory systems and are also content providers, who sense and share diverse and relevant raw spatial-temporal data (HUI; SHERRATT, 2017; NAHA *et al.*, 2018; PHUTTHARAK; LOKE, 2019). Accordingly, sensors and actuators can be classified as follows:

3.2.2.1.1 Physical sensors

Physical sensors are tangible devices that sensor and generate sensor data. The data retrieved from physical sensors represent a low-level context (PERERA *et al.*, 2014). Examples of physical sensors are temperature sensors, pressure sensors, biosensors, light sensors (SRINIVAS; JABBAR; NEERAJA, 2018), and human sensors (HALLER *et al.*, 2013).

3.2.2.1.2 Cyber or virtual sensor

A cyber sensor is an abstract information entity that serves sensor function but does not directly interact with the physical world. Cyber sensor examples are computer programs and systems, communication processes, and monitoring activities that have no physical body (e.g., sensing web service) (CHAOCHAISIT *et al.*, 2016; GAO; LEI; YU, 2015; OBERLÄNDER *et al.*, 2018). It retrieves data from many sources and publishes them as sensor data. They commonly use web services technology to send and receive data (PERERA *et al.*, 2014).

3.2.2.1.3 Cyber-physical sensors

Logical sensors or software sensors: These connect the cyber and physical worlds as a combination of physical sensors and virtual sensors to produce meaningful information (BERGER; DENNER; RÖGLINGER, 2018; YAQOOB *et al.*, 2017). They commonly use web services technology to send and receive data (PERERA *et al.*, 2014). They are autonomous, cyber-physical objects augmented with sensing/actuating, processing, storing, and networking capabilities (FORTINO *et al.*, 2014).

3.2.2.2 Nature

The nature dimension refers to sensor knowledge, intertwined with its architecture and functionality (BHATT; PATWA; SANDHU, 2017). A sensor is anything that observes (COMPTON *et al.*, 2012). Humans are content receivers through the sensory systems, but they are also content providers — mainly through muscular movements and nervous systems (HUI; SHERRATT, 2017; MONTORI *et al.*, 2018), and through tacit knowledge and experiences that can affect their actions in IoE applications and cognitive tasks. People can be modeled as sensors (RUSSELL; NORVIG; DAVIS, 2016) and anything that acts individually to perform a task is an individual IoE sensor device (NAHA *et al.*, 2018). Knowing the nature of knowledge source devices is crucial for publication, discovery, sharing, reuse, and integration of data/information within the IoE/IoT environment (ROZSA *et al.*, 2016). Human beings with dedicated roles, as well as machines, devices, and services (ATAT *et al.*, 2018; BARKER *et al.*, 2014; HALLER *et al.*, 2013), implies system constraints when it interacts with the physical space (CHEN; HELAL, 2011).

Several works have identified sensor types according to the type of sensing they are based on and the data type collected (ARMANDO *et al.*, 2018; HARON *et al.*, 2017; SINCHE *et al.*, 2019).

According to their built-in nature, sensors in IoE are classified (ARMANDO *et al.*, 2018) as follows:

3.2.2.2.1 Electronic-based sensors

Define physical IoT devices, based on electronic or mechanical systems that measure physical variables and actuate physical phenomena.

3.2.2.2.2 Software-based sensors

Define virtual entities that produce information from the repository or analytical results, using some processing techniques.

3.2.2.2.3 Human-based sensors

Define humans or virtual entities, based on knowledge provided or reported by human judgment about any phenomena occurring in their physical, virtual, or social environment.

3.2.2.2.4 Non-human-based sensors

Define biotic sensors based on knowledge data provided by biotic sensors about any phenomena occurring in their physical environment. In the constantly growing area of animal cognition, sensor networks monitor health and welfare in non-human animals in livestock herds and animal surveillance applications (RAVIGNANI *et al.*, 2013).

3.2.2.3 Use

Refers to the physical characteristics of the physical IoE sensors, related to their usage in a particular application. The devices inherit the properties of their owners or of the entities or platform (AGARWAL *et al.*, 2016) to which they are attached (BHATT; PATWA; SANDHU, 2017; BOYES *et al.*, 2018; CHAOCHAISIT *et al.*, 2016). A wide variety of objects — a group of infrastructures and devices (DORSEMAINE *et al.*, 2015) such as embedded devices, sensors, service, radio-frequency identification (RFID), and actuators — have integrated communication and, depending on its usage, provides tight interactions to create a pervasive environment (ATAT *et al.*, 2018; BARKER *et al.*, 2014; QANBARI *et al.*, 2015).

Smutný (SMUTNÝ, 2016) described things according to how they are used or applied to humans:

3.2.2.3.1 Embeddable

Embeddable devices are sensors that are in the user or under the user's skin, that are non-autonomous, or embedded in carry-on devices (OBINIKPO; KANTARCI, 2017). Its autonomy level ranges from human-companion device tasks (PHUTTHARAK; LOKE, 2019) to opportunistic devices, which decide and act independently (ALKHABBAS; SPALAZZESE; DAVIDSSON, 2019; ERIS; DRURY; ERCOLINI, 2015). For example, a mobile phone is a user-friendly device and has many sensors embedded (SETHI; SARANGI, 2017), which is why it has turned into a global mobile sensing device (SALIM; HAQUE, 2015).

3.2.2.3.2 Wearable

Wearables sensors are devices that rest on a person's body or can be used, worn, or attached to their owners, and enable accurate detection of the wearers' motions

(BUGEJA; DAVIDSSON; JACOBSSON, 2018; HUI; SHERRATT, 2017; SUBBU; VASILAKOS, 2017; YEBDA *et al.*, 2019).

3.2.2.3.3 Surroundables

Surroundables sensors are autonomous devices, near or around the user, but which have no physical contact with the user. Non-contact sensing can detect information without direct contact with a subject, and without devices physically touching the body. Non-contact techniques have been considered highly valuable in dealing with highly infectious diseases such as COVID-19 (TAYLOR *et al.*, 2020).

3.2.2.4 Role

Smart devices have sensing and actuating capability according to defined rules under various scenarios (NAHA *et al.*, 2018; ROZSA *et al.*, 2016). They perform sensing and actuating functions (ALKHABBAS; SPALAZZESE; DAVIDSSON, 2019; MOUNTROUIDOU; BILLINGS; MEJIA-RICART, 2019; OBERLÄNDER *et al.*, 2018) in interactions with the physical environment (SETHI; SARANGI, 2017). An IoE device or enabler can be a sensor, an actuator, or a sensor and actuator (ATAT *et al.*, 2018; DORSEMAINE *et al.*, 2015; MOUSTAKA; VAKALI; ANTHOPOULOS, 2018).

3.2.2.4.1 Sensor

A sensor is a monitor device that observes and senses and provides the information required to immediately control actuators; whereas actuators act on the physical entity or control other things (ERIS; DRURY; ERCOLINI, 2015; HALLER *et al.*, 2013; SIOW; TIROPANIS; HALL, 2018a). Sensing is a read operation over a context entity. The data collected by a sensor is stored and processed intelligently to derive useful inferences and to support the decision-making process (CHEN; HELAL, 2011).

3.2.2.4.2 Actuator

Actuators act and affect a particular domain of the physical space or a combination of both. Actuation is a write operation over a context entity, in which the conceptual entity represents the domain of a sensor or an actuator (DORSEMAINE *et al.*, 2015). Actuators perform the decided actions and effect a change in the environment (BELLAVISTA; BERROCAL, 2019; PERERA *et al.*, 2014; SETHI; SARANGI, 2017).

3.2.2.4.3 Sensor and actuator

This device is a hybrid of the two previous categories, and it can gather data and act within its environment.

Processing and analytics (fixed process or algorithm, machine learning, or AI) don't fit within this classification (BOYES *et al.*, 2018).

3.2.2.5 Engagement

Engagement refers to sensing tasks. In data acquisition, it can be both opportunistic and participatory, and it provides sensory information that collectively forms knowledge in distinct engagement levels.

Cooperative smart things can interact with other constituents of the IoE to work toward a unified objective (LANGLEY *et al.*, 2020) and with humans in real-time ubiquitous computing (HUI; SHERRATT, 2017; OTEAFY; HASSANEIN, 2019). The engagement of a sensor node in an IoE application is one of the following:

3.2.2.5.1 Participatory

The sensor or actuator device is actively involved and actively reports observations (MONTORI *et al.*, 2018). It can retrieve information about the environment, weather, urban mobility, and congestion, as well as any other sensory information that could be on social groups (social sensing) or with everyone (public sensing) or at the community level (ATAT *et al.*, 2018; HARON *et al.*, 2017; SALIM; HAQUE, 2015). With mobile crowdsourcing, the primary information shared voluntarily is user knowledge and opinion, along with location as the only sensor information (PHUTTHARAK; LOKE, 2019).

3.2.2.5.2 Opportunistic

The sensor or actuator device has minimal or no involvement — it senses and monitors tasks running in the background. Embedding sensors trigger the data automatically (either periodically or based on events).

3.2.3 Observation

The Observation category contains five subcategories related to sensed context and monitoring activities: Location, Reach, Mobility, Time, and Mode.

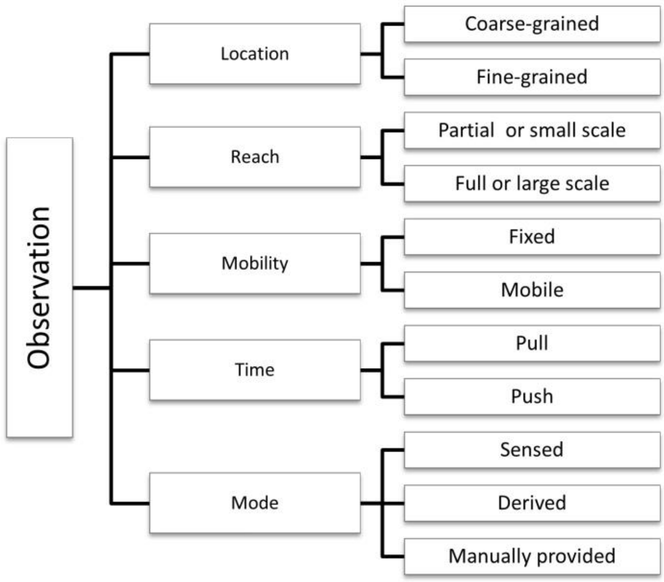


Figure 15. Observation Category, its dimensions, and characteristics

3.2.3.1 Location

The location dimension refers to the spatial context (physical context) of IoE sensors within a local or global network (ALKHABBAS; SPALAZZESE; DAVIDSSON, 2019; BAJAJ *et al.*, 2018; BOYES *et al.*, 2018; MOUNTROUIDOU; BILLINGS; MEJIA-RICART, 2019; SHOLLA; NAAZ; CHISHTI, 2017). It represents the geophysical position of a sensor or actuator in absolute terms, specifying the coordinates (latitude and longitude) or relative terms through location tags (FORTINO *et al.*, 2014) or an area covered by a particular object (AGARWAL *et al.*, 2016). Sensors that are randomly deployed get the required information about the target environment (SAAD; ELHOSSEINI; HAIKAL, 2018), obtained manually or automatically (MONTORI *et al.*, 2018). The location-aware aggregation of knowledge patterns facilitates reduced data transfer in remote environments and minimizes bandwidth use (UR REHMAN *et al.*, 2017). Location systems — both outdoor and indoor — can be categorized as context-aware systems (SUBBU; VASILAKOS, 2017).

The precise location of an object is critical since location plays a significant role in context-aware computing (CHAOCHAISIT *et al.*, 2016; PERERA *et al.*, 2014; SHIT *et al.*, 2018). Some physical measurement-based localization schemes are classified as coarse-grained and fine-grained (SHIT *et al.*, 2018).

3.2.3.2 Reach

When related to KM, reach classification distinguishes between individual and collective knowledge as well as novel classifications, such as collective knowledge classified into individual or group, internal or external, full, or partial domains (Prat, 2006). In IoE, it refers to an environment of sensing interest (QANBARI *et al.*, 2015). Sensors are getting more powerful, cheaper, and smaller in size, due to sensor technology advances, stimulated large-scale deployments (PERERA *et al.*, 2014), and dense geographical distribution (HASSAN *et al.*, 2018).

The domain of interest represents the applicative domain in which the device is operative (AGARWAL *et al.*, 2016; SAAD; ELHOSSEINI; HAIKAL, 2018), and ensures that IoT services are accessible or reached only by authorized access (ABDUL-GHANI; KONSTANTAS; MAHYOUB, 2018; BOYES *et al.*, 2018).

For instance, a conglomerate of sensor network data stored on a cloud storage infrastructure can be referred to as big data sensing and based on the reach of its sensing requests and requirements (GAO; LEI; YU, 2015), it can be: a) private big data sensing, b) public big data sensing, c) community big data sensing, or d) hybrid big data sensing.

3.2.3.3 Mobility

Mobility or monitoring continuity (PERERA *et al.*, 2014), is one of the main characteristics that enables identification of the state of sensors and actuators and their capability of movement (BELLAVISTA; BERROCAL, 2019; BHATT; PATWA; SANDHU, 2017; BOYES *et al.*, 2018; DORSEMAINE *et al.*, 2015; HASSAN *et al.*, 2018; MAHDAVINEJAD; REZVAN; BAREKATAIN, 2018; MOUNTROUIDOU; BILLINGS; MEJIA-RICART, 2019; PERERA *et al.*, 2014; SETHI; SARANGI, 2017; SHIT *et al.*, 2018; SINCHE *et al.*, 2019), with significant implications on device operation, connectivity, and location management (SETHI; SARANGI, 2017; SHIT *et al.*, 2018; SINCHE *et al.*, 2019). Devices are classified into two categories: static/immobile/fixed and mobile (BOYES *et al.*, 2018; MOUNTROUIDOU;

BILLINGS; MEJIA-RICART, 2019; MOUSTAKA; VAKALI; ANTHOPOULOS, 2018; POZZA *et al.*, 2015).

3.2.3.3.1 Fixed/static/immobile

Fixed devices are those that remain static to a specific location or cannot move. Their observations are restricted to a specific location, in a static or very constrained (in terms of mobility) environment that is not designed to move (relative to their point of installation) without being uninstalled.

3.2.3.3.2 Mobile

Mobile objects are devices that move (DORSEMAINE *et al.*, 2015), and their location may be calculated in absolute coordinates or relative to reference nodes in the network (SAAD; ELHOSSEINI; HAIKAL, 2018), requiring a wireless communications mechanism to convey data and permit configuration and control (BOYES *et al.*, 2018). Their movement and mobility capability are controlled independently (or autonomously) or dependently through device users (BHATT; PATWA; SANDHU, 2017).

In crowdsensing applications, mobility of the things in the system is dependent on the collaboration of the items physically coupled with the humans in the system (ERIS; DRURY; ERCOLINI, 2015). In this application, in which geographically dispersed users actively (participatory) or passively (opportunistic) collect data with their smartphones (OBERLÄNDER *et al.*, 2018; SUBBU; VASILAKOS, 2017). Classifications between mobility-agnostic and mobility-aware (POZZA *et al.*, 2015) highlight an approach that ignores knowledge about mobility and the ones that consider and exploit it for optimization (SRINIVASAN *et al.*, 2019).

Challenges related to mobility include frequent disconnections and handoffs, which affect perfect connectivity (NAYYER; RAZA; HUSSAIN, 2019). So mobility techniques in the cloud, fog, and edge architectures (HASSAN *et al.*, 2018) support mobility (BELLAVISTA; BERROCAL, 2019).

3.2.3.4 Time

Time represents the instant of observation (i.e., timestamp) (AGARWAL *et al.*, 2016). Information about time and location are critical features of some applications (called spatial-temporal-aware applications) that require tasks to make observations at a specific location during a defined period (MONTORI *et al.*, 2018). In (ALKHABBAS; SPALAZZESE; DAVIDSSON, 2019), latency characterizes aspects related to the time an IoE system needs to respond to a stimulus or to complete a task. It is the response time (ASGHARI; RAHMANI; JAVADI, 2018, 2019; CAI *et al.*, 2018).

The time dimension depends on how sensors are requested and respond to the system in specific periods or on an ad-hoc basis (as software system makes a request), which is characterized as the following two distinct methods that were proposed in (CAI *et al.*, 2018):

Pull method: The software component responsible for acquiring sensor data from sensors makes a request periodically (after certain intervals) or instantly acquires data on an ad-hoc basis (CAI *et al.*, 2018).

Push method: The physical or virtual sensor pushes data to the software component responsible for acquiring sensor data periodically or instantly (CAI *et al.*, 2018; PERERA *et al.*, 2014). A sensor observation could be the outcome of a local sensor data fusion (BISDIKIAN; KAPLAN; SRIVASTAVA, 2013).

Real-time applications monitor the state of the environment and react to changes accordingly and promptly and its responsiveness (low-latency and real-time interactions) is a challenge for IoE applications and their deployment in real-world scenarios. The coherency between the value of the data in the system and its corresponding environment state is temporal data consistency (CAI *et al.*, 2018). In dynamic and real-time scenarios, inferred contexts evolve with time (BAJAJ *et al.*, 2018; UR REHMAN *et al.*, 2017), and the exchanged data from and to the cloud might not be accurate, because of the high latency during interactions (BELLAVISTA; BERROCAL, 2019). Hard real-time data cannot tolerate any delay, whereas soft real-time data can tolerate several bounded delays. Delay-tolerant applications can be classified as non-real-time (CAI *et al.*, 2018; HASSAN *et al.*, 2018) (HARON *et al.*, 2017; PHUTTHARAK; LOKE, 2019).

Timeliness (CAI *et al.*, 2018; SHAH *et al.*, 2019) (i.e., data processing rate by a given deadline), which is real-time/static, near real-time, or batch processing (BOYES *et al.*, 2018).

Real-time: refers to immediate computation processing for a time-sensitive application, with results in seconds, as follows:

Near real-time: It refers to situations when the computation process is not as immediate as real-time, but time is still relevant.

Batch-processing: It refers to situations when data are first collected, and processed only when a specified amount of data is available or at a predetermined interval (HARON *et al.*, 2017).

3.2.3.5 Mode

The mode dimension refers to the smart sensor's activities (active or passive), depending on their usage and functionalities (MASOUD *et al.*, 2019; PHUTTHARAK; LOKE, 2019). The combination of sensors serving different purposes and data generated in IoE applications implies the need to classify data sources and information in the IoT context (ROZSA *et al.*, 2016). During real-time data harvesting, it can be challenging to determine the possible relationships among heterogeneous knowledge sources (SHAH *et al.*, 2019).

Eris *et al.* (ERIS; DRURY; ERCOLINI, 2015) defined how much interaction is required within the network in three levels of collaboration interdependence (ERIS; DRURY; ERCOLINI, 2015):

Pooled interdependence: The lowest level of collaboration, in which each collaborator makes a discrete contribution to the collaboration environment. Each collaborator benefits from the contributions of others. The collaborators do not have to synchronize their contributions or negotiate the nature of each other's contributions.

Sequential interdependence: The middle level of collaboration, in which the output of one collaborator becomes the input to another collaborator, which demands a temporal ordering of the collaboration efforts.

Reciprocal interdependence: The highest interdependence level of collaboration, in which one collaborator's outputs are the next collaborator's inputs, and collaborators must also deal with contingencies between their contributions to the collaboration environment.

The Mode dimension refers to the way of linking the physical and digital world, to acquire context (MON *et al.*, 2018), and it can be either sensed, derived, or manually provided:

Sensed: Includes the sensed data gathered through sensors.

Derived: Includes the sensed data stored in databases or the information generated by performing computational operations on sensor data. Data aggregation serves as a pillar of the application's workflow and directly impacts the software system's quality. (CAI *et al.*, 2018).

Manually provided: Human sensors provide the context information (PERERA *et al.*, 2014).

3.2.4 Capabilities

The *Capabilities* category contains three subcategories (Communication, Processing, and Storage), and refers to the processing power and storage capacity of the underlying technologies and communication protocols.

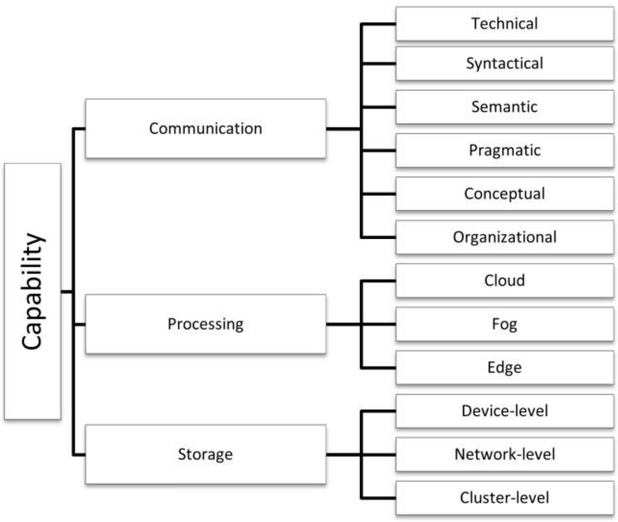


Figure 16. Capability, its dimensions, and characteristics

3.2.4.1 Communication

Communication capability refers to the sensors' ability to communicate and change information locally. This ability may vary at different levels of interoperability between IoE sensors and systems, and be classified as no connection (no interoperability between enablers), technical (basic connectivity and network connectivity), syntactical (data exchange interoperability), semantic (understanding in the meaning of the data), pragmatic/dynamic (applicability of the information), or conceptual (shared view of the world) (NOURA; ATIQUZZAMAN; GAEDKE, 2019). Additionally, based on communication capabilities, IoT devices are classified into two categories: gateway devices and constrained devices (BHATT; PATWA; SANDHU, 2017; FORTINO *et al.*, 2014). And according to their abilities to interact with other objects, IoT objects can be classified into four levels (Level 0–Level 3). Level 0 only receives, and Level 1 objects only send information. Level 2 objects can perform both operations with one object, while Level 3 extends the interaction to any other object (BUGEJA; DAVIDSSON; JACOBSSON, 2018).

Distinct networking protocols and technologies provide networking interoperability in IoT (NOURA; ATIQUZZAMAN; GAEDKE, 2019; SETHI; SARANGI, 2017; SIOW; TIROPANIS; HALL, 2018a). IoT networks have different characteristics in terms of size, data transfer, coverage, latency requirements, capacity, and supported reachability (BARKER *et al.*, 2014; BERGER; DENNER; RÖGLINGER, 2018; GAO; LEI; YU, 2015; SHAH *et al.*, 2019; SUBBU; VASILAKOS, 2017). Some networking and communication technologies are local area networks, wireless local area networks, wireless personal area networks, wide area networks, metropolitan area networks, wireless regional area networks, body area networks, mobile communication networks, wireless metropolitan area networks, satellite networks (e.g., GPS) (AHMED *et al.*, 2016; ALKHABBAS; SPALAZZESE; DAVIDSSON, 2019; MEHMOOD *et al.*, 2017), Neul, IPv6 over Low-power Personal Area Networks (6LowPAN), low-range wireless area networks, cellular Sigfox, narrowband-IoT, and Thread or mesh technologies such as Zigbee and SDNs (BOYES *et al.*, 2018; SINCHE *et al.*, 2019; YAQOOB *et al.*, 2017).

The communication protocols that enable IoT to interconnect and communicate, and are classified as: (1) Device to Device, which is applied to communication between mobile phones nearby, and represents the next generation of cellular networks; (2) Device to Server, in which the data is sent to the servers, close or far away from devices (applies to cloud processing); and (3) Server to Server, in which servers transmit data between each other — mainly used for cellular networks (MAHDAVINEJAD; REZVAN; BAREKATAIN, 2018).

3.2.4.2 Processing

The sensors and devices vary in their processing capabilities (FAN *et al.*, 2015). The study of (MON *et al.*, 2018) classifies sensors as high-end or low-end devices, depending on resources and computational capabilities. Low-end devices are resource-constrained in terms of energy, processing power, and communication capabilities. The processing capability is the sensors' ability to process aggregated data locally (ALSAMANI; LAHZA, 2018).

Data processing techniques are either historical or proactive. Historical data processing is related to knowledge discovery; whereas proactive data processing provides predictive and actionable insights (ALKHABBAS; SPALAZZESE; DAVIDSSON, 2019).

Analytics technology refers to the systematic computational analysis of transforming a variety of data from different sources into information (MOHAMED *et al.*, 2019), and applying data fusion and mining techniques (UR REHMAN *et al.*, 2017) to make intelligent decisions at the following distribution levels: (1) the device level, where devices act as data producers and as participants of the storage and computing process; (2) the network level, which involves remote connections to fog computing nodes, hubs, base stations, gateways, routers, and servers; and (3) cloud level, within a group of interconnected servers (AHMED *et al.*, 2016; ALKHABBAS; SPALAZZESE; DAVIDSSON, 2019; GLUHAK *et al.*, 2011; SIOW; TIROPANIS; HALL, 2018a; YAQOOB *et al.*, 2016).

Cloud, edge and fog computing are integral parts of the centralized and decentralized IoE ecosystem (MOUNTROUIDOU; BILLINGS; MEJIA-RICART, 2019; SMUTNÝ, 2016; YAQOOB *et al.*, 2017). Since devices that have low compute and memory capacity need to delegate these functions, edge computing can efficiently handle the processing problems associated with edge big data. In the edge computing paradigm, the data is close to or at the edge of the network (ERIS; DRURY; ERCOLINI, 2015; ZHANG *et al.*, 2018).

Related expansions of cloud computing and edge computing paradigms are mobile cloud computing (MCC), cloudlets, mobile edge computing (MEC), and fog computing (FC) (HASSAN *et al.*, 2018; NAYYER; RAZA; HUSSAIN, 2019; NEZAMI; ZAMANIFAR, 2019). Cloudlets, MEC, and FC are edge computing technologies and rely on virtualization; while MCC processes the data of rich mobile applications, outside the mobile devices at a remote cloud data center.

3.2.4.3 Storage

The storage dimension refers IoE system's storage function, based on the paradigm where its storage function resides: cloud, fog, or edge (YAQOOB *et al.*, 2016). A storage platform (public, virtual, or private) offers the flexibility and scalability that an IoE application needs, from development to deployment (SMUTNÝ, 2016). Storage refers to storing data internally, and it varies intensively from one object to another (ALSAMANI; LAHZA, 2018). Storage interactions between IoE enablers may differ significantly depending on the object's capabilities. Some objects may have very few capabilities and store minimal information (USCHOLD, 1996). Most mobile devices at the edge of the network are resource-constrained, with low storage capability (ZHANG *et al.*, 2018). Although almost all of the IoT devices can store embedded codes to function internally, they differ in storing aggregated and processed data (PAL; VANIJJA; VARADARAJAN, 2018). An object's storage should also be based on the sensitivity of the information stored (ALSAMANI; LAHZA, 2018).

Depending on the storage and compute capabilities, the storage capability of an IoE node or application is classified as follows (SIOW; TIROPANIS; HALL, 2018a):

- Device-level: devices act not just as data producers but as participants in the storage and compute process.
- Network-level: the storage function uses remote connections to fog computing nodes, hubs, base stations, gateways, routers, and servers.
- Cluster level: storage function is provided within a group of interconnected servers (SIOW; TIROPANIS; HALL, 2018a).

3.3 Taxonomy evaluation

This section presents the IoE Knowledge-based taxonomy conceptual validation. It aimed to show that the proposed taxonomy involves the qualitative attributes of robustness and comprehensiveness. It contains enough dimensions and characteristics to differentiate the objects of interest into distinct domains, and to classify all known objects within the field under consideration (NICKERSON; VARSHNEY; MUNTERMANN, 2013)`

There is a brief comparison of the scope of the proposed IoE taxonomy and 76 IoE and IoT taxonomy previous works, selected in the literature review (presented in Section 3.1). Diverse approaches were examined to enhance understanding of the contextual aspects of IoE/IoT addressed and their relationships in knowledge management in IoE/IoT applications.

The comparison presented in Table 4 shows the adherence of the analyzed studies to our proposed IoE taxonomy, across the proposed categories and dimensions. Concerning dimensions of the IoE taxonomy, *Capabilities* is the category most frequently addressed and studied, followed by *Observation* and *Type* of sensor, respectively. Previous works were compared, and the summaries show that most taxonomies support at least two categories, but *Knowledge* support is limited.

The proposed IoE Knowledge-based taxonomy covered all the 18 categories (100%). On average, it should be noted that the remaining 76 studies, covered 25,5% of the categories. The framework proposed by Boyes and Hallaq (BOYES *et al.*, 2018) obtained the second-highest coverage (72%), with 13 categories; however, it did not include aspects related to the type of knowledge in IoE applications. On average, the *Knowledge* category obtained 24,7% coverage; while the *Type* of sensor, *Observation* and *Capabilities* categories appeared in 20.5, 20, and 44.3% of the studies, respectively.

The results demonstrated a few interest (only 15.8%) in identifying knowledge sources in terms of explicitness (tacit, explicit, or implicit). And only 13.1% of the studies addressed how the outcome of the IoE application was achieved and benefited by complementation (accompaniment) or substitution (replacement) of knowledge in IoE processes (between things, data, and humans). Thus, further research should consider this gap and attempt to examine the impact of knowledge identification on the design of IoE applications, and how knowledge should be synthesized and combined to drive knowledge creation and intelligent services that create value. In this sense, Section 3.4 will present the IoE Integrated KM Model. In conclusion, the findings of this present study provided an insight into the current trend of IoE research.

Table 4. Comparison of the scope of IoE Knowledge-based paradigm with previous works

Category		Knowledge					Type					Observation					Capabilities		
Dimensions		Explicitness	Structure	Trust	Outcome	Action	Presentation	Nature	Use	Role	Engagement	Location	Reach	Mobility	Time	Mode	Communication	Processing	Storage
Ref.	Year																		
This study	**2020**	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
(ALKHABBAS; SPALAZZESE; DAVIDSSON, 2019)	2019					✓		✓	✓	✓		✓			✓		✓		
(MOUNTROUIDOU; BILLINGS; MEJIA-RICART, 2019)	2019									✓		✓		✓			✓	✓	
(NOURA; ATIQUZZAMAN; GAEDKE, 2019)	2019		✓	✓													✓		
(SINCHE *et al.*, 2019)	2019						✓	✓						✓			✓	✓	✓
(OTEAFY; HASSANEIN, 2019)	2019				✓	✓					✓						✓	✓	
(AHAD; TAHIR; YAU, 2019)	2019			✓													✓		
(BELLAVISTA; BERROCAL, 2019)	2019			✓		✓	✓			✓				✓	✓		✓	✓	✓
(YEBDA *et al.*, 2019)	2019		✓	✓					✓										
(PHUTTHARAK; LOKE, 2019)	2019			✓	✓		✓		✓		✓		✓		✓	✓	✓		
(SHAH *et al.*, 2019)	2019		✓	✓		✓									✓	✓	✓		
(SAHINEL *et al.*, 2019)	2019				✓		✓												
(BONTE *et al.*, 2019)	2019	✓	✓				✓												
(MOHAMED *et al.*, 2019)	2019		✓			✓												✓	✓
(CAI *et al.*, 2018)	2019		✓												✓	✓			
(ASGHARI; RAHMANI; JAVADI, 2019)	2019			✓		✓									✓				
(NESHENKO *et al.*, 2019)	2019			✓													✓	✓	✓
(NAYYER; RAZA; HUSSAIN, 2019)	2019													✓			✓	✓	

Category		Knowledge					Type					Observation					Capabilities		
Dimensions		Explicitness	Structure	Trust	Outcome	Action	Presentation	Nature	Use	Role	Engagement	Location	Reach	Mobility	Time	Mode	Communication	Processing	Storage
Ref.	Year																		
(ARMANDO *et al.*, 2018)	2018						✓		✓										
(HARON *et al.*, 2017)	2018			✓				✓			✓				✓				
(ALSAMANI; LAHZA, 2018)	2018			✓	✓	✓												✓	✓
(ZHANG *et al.*, 2018)	2018			✓														✓	✓
(NAHA *et al.*, 2018)	2018						✓			✓							✓	✓	✓
(HASSAN *et al.*, 2018)	2018			✓		✓						✓	✓	✓	✓		✓	✓	✓
(ASGHARI; RAHMANI; JAVADI, 2018)	2018			✓											✓		✓		
(BUGEJA; DAVIDSSON; JACOBSSON, 2018)	2018		✓						✓								✓		
(OBERLÄNDER *et al.*, 2018)	2018				✓	✓	✓			✓				✓			✓		
(GE; BANGUI; BUHNOVA, 2018)	2018	✓	✓																
(SHIT *et al.*, 2018)	2018											✓	✓	✓			✓		
(SAAD; ELHOSSEINI; HAIKAL, 2018)	2018											✓	✓	✓					
(BERGER; DENNER; RÖGLINGER, 2018)	2018						✓	✓									✓		
(MAHDAVINEJAD; REZVAN; BAREKATAIN, 2018)	2018	✓	✓											✓			✓	✓	
(RUTA *et al.*, 2018)	2018	✓	✓																
(PAL; VANIJJA; VARADARAJAN, 2018)	2018		✓	✓	✓	✓			✓								✓	✓	✓
(ATAT *et al.*, 2018)	2018		✓	✓		✓		✓	✓	✓	✓						✓	✓	✓
(BOYES *et al.*, 2018)	2018			✓	✓	✓		✓	✓	✓		✓	✓	✓	✓		✓	✓	✓
(SIOW; TIROPANIS; HALL, 2018a)	2018		✓	✓						✓							✓	✓	✓
(ABBAS *et al.*, 2018)	2018			✓								✓	✓				✓		
(MOUSTAKA; VAKALI; ANTHOPOULOS, 2018)	2018				✓					✓				✓			✓		

Category		Knowledge					Type					Observation					Capabilities		
Dimensions		Explicitness	Structure	Trust	Outcome	Action	Presentation	Nature	Use	Role	Engagement	Location	Reach	Mobility	Time	Mode	Communication	Processing	Storage
Ref.	Year																		
(MONTORI *et al.*, 2018)	2018							✓			✓	✓			✓	✓			
(ABDUL-GHANI; KONSTANTAS; MAHYOUB, 2018)	2018											✓	✓				✓	✓	✓
(MON *et al.*, 2018)	2018																✓	✓	
(YAQOOB *et al.*, 2017)	2017				✓	✓											✓	✓	
(SHAHID; ANEJA, 2017)	2017	✓															✓	✓	✓
(OBINIKPO; KANTARCI, 2017)	2017	✓	✓			✓			✓		✓								
(BHATT; PATWA; SANDHU, 2017)	2017								✓					✓			✓	✓	
(SHOLLA; NAAZ; CHISHTI, 2017)	2017			✓								✓					✓		
(HUI; SHERRATT, 2017)	2017	✓			✓		✓	✓	✓		✓								
(SETHI; SARANGI, 2017)	2017								✓	✓		✓		✓			✓	✓	
(MARJANI *et al.*, 2017)	2017		✓	✓		✓												✓	✓
(SUBBU; VASILAKOS, 2017)	2017								✓			✓		✓				✓	✓
(AGARWAL *et al.*, 2016)	2017						✓		✓	✓		✓	✓		✓				
(UR REHMAN *et al.*, 2017)	2017	✓	✓									✓	✓	✓	✓		✓	✓	✓
(HÖLLER; TSIATSIS; MULLIGAN, 2017)	2017	✓	✓	✓		✓													
(AKOKA; COMYN-WATTIAU; LAOUFI, 2017)	2017		✓																
(SMUTNÝ, 2016)	2016								✓									✓	✓
(DORSEMAINE *et al.*, 2015)	2016								✓	✓				✓			✓		
(CHAOCHAISIT *et al.*, 2016)	2016	✓					✓		✓			✓							
(ROZSA *et al.*, 2016)	2016								✓	✓		✓				✓			
(YAQOOB *et al.*, 2016)	2016		✓															✓	✓
(BOTTA *et al.*, 2016)	2016			✓													✓	✓	✓

Category		Knowledge					Type					Observation					Capabilities		
Dimensions		Explicitness	Structure	Trust	Outcome	Action	Presentation	Nature	Use	Role	Engagement	Location	Reach	Mobility	Time	Mode	Communication	Processing	Storage
Ref.	Year																		
(CHELLAPPAN; SIVALINGAM, 2016)	2016			✓													✓	✓	✓
(AHMED *et al.*, 2016)	2016					✓											✓		
(ERIS; DRURY; ERCOLINI, 2015)	2015		✓				✓		✓	✓			✓	✓		✓	✓		
(ASHRAF; HABAEBI, 2015)	2015			✓			✓										✓		
(SALIM; HAQUE, 2015)	2015						✓		✓		✓								
(QANBARI *et al.*, 2015)	2015		✓						✓				✓						
(GAO; LEI; YU, 2015)	2015		✓				✓						✓			✓	✓	✓	✓
(POZZA *et al.*, 2015)	2015	✓										✓		✓	✓	✓			
(FORTINO *et al.*, 2014)	2014			✓						✓		✓					✓		
(PERERA *et al.*, 2014)	2014	✓	✓			✓	✓			✓		✓	✓	✓	✓		✓		
(JING *et al.*, 2014)	2014			✓													✓		
(BARKER *et al.*, 2014)	2014			✓				✓	✓						✓		✓		
(HALLER *et al.*, 2013)	2013						✓	✓		✓									
(BISDIKIAN; KAPLAN; SRIVASTAVA, 2013)	2013		✓	✓		✓									✓		✓	✓	
(CHEN; HELAL, 2011)	2011			✓			✓	✓		✓									
(GLUHAK *et al.*, 2011)	2011																✓	✓	✓

Additionally, the IoE taxonomy was validated using a sample of analyses of 50 applications, the full results and details are available in a dataset within a technical report (https://www.cos.ufrj.br/uploadfile/publicacao/2963.pdf).

3.4 IoE Integrated Knowledge Management Model (IoE IKM Model)

The development of a specific knowledge management model to support knowledge creation in IoE applications can provide an adequate set of concepts to support knowledge management by design and implementation of knowledge management strategy considering M2P, M2M and P2P collaboration.

In Section 2.3, the Knowledge Management concepts and models were analyzed from a comparative perspective, keeping in mind the definition of a generic knowledge management model with high applicability in the context of IoE.

Gao *et al.* (GAO; CHAI; LIU, 2017) reviewed the definitions about KM and conclude that despite the vast amount of definitions and descriptions about KM, the essence of KM is to support learning efficacy and integration of different information resources to improve competitiveness advantages.

IoE is about intelligent services to support a dynamic ubiquitous environment. Section 2.4 highlighted an e-governance knowledge management approach for intelligent service in IoE applications (Figure 9). The focus is leveraging awareness of intelligence sources (on perception layer) and supporting self-organization and collective action (on governance layer) for knowledge aggregation (on KM layer).

The Hierarchical Model for Knowledge Management proposed by Prat (PRAT, 2011) provides an effective conceptual representation of knowledge management from a strategic point of view and proved to be adequate for distinguishing knowledge management processes between strategic processes and operational processes, making it possible to abstract the concepts of value and trust (more strategic point of view regarding knowledge identification and evaluation), from the way knowledge is managed, shared and stored. The evaluation process guides the evaluation of knowledge, knowledge systems and projects, and Knowledge Management (the KM strategy). However, this Model lacks an evolutionary approach that leads to intelligent services improvement in the IoE context. Figure 17 presents the Hierarchical Model for Knowledge Management proposed by Prat (PRAT, 2011).

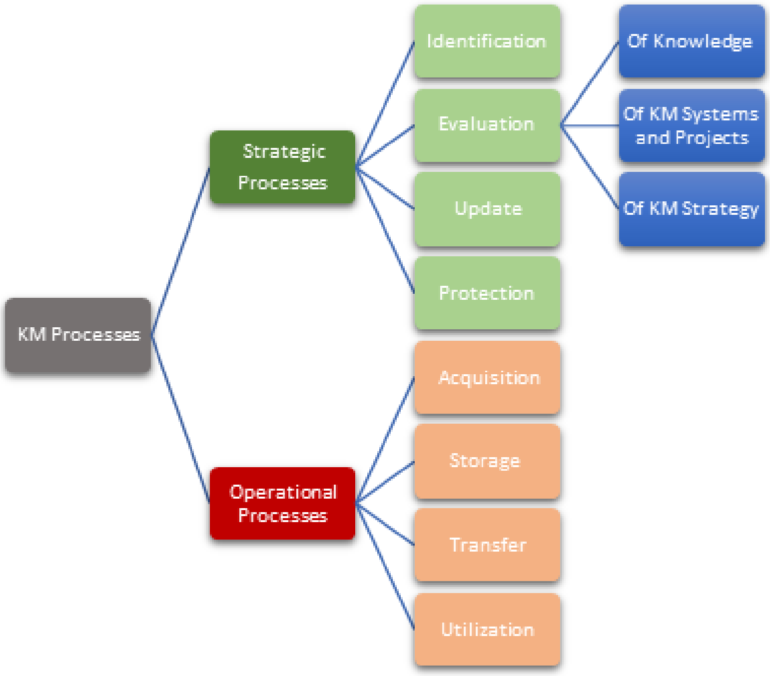


Figure 17. Hierarchical Model of Knowledge Management, adapted from Prat (2011)

This thesis proposes integrating service science and knowledge management research to support the e-governance of IoE applications for intelligence service evolution towards goal-directed actions. For this, the proposed IoE Integrated Knowledge Management Model (IoE IKM Model) leverages awareness of intelligence sources in IoE applications, considering IoE enablers, observation capabilities, supporting e-governance and knowledge creation.

The IoE Integrated Knowledge Management Model (IoE IKM Model), as the contribution of this work, integrates the knowledge creation model (SECI process) (NONAKA; KONNO, 1998) and service evolution cycles (SERI cycle) (KIM, 2019), to support the design of intelligent services centered around the process of creating knowledge and value in the IoE context.

The integration of knowledge creation and service operation model (NONAKA; KONNO, 1998)(KIM, 2019) promotes service enhancement and self-improvement of IoE enablers in faster evolution cycles centered around knowledge processes for value co-creation.

This thesis approach will consider strategic and operational KM processes proposed by (PRAT, 2011) applied to service evolution cycles (SERI cycle) (KIM, 2019). And for evaluation purposes, the artifacts presented in this thesis will support:

- The identification and evaluation of knowledge, knowledge projects, and systems: the proposed IoE Knowledge-based Taxonomy (Section 3.2) and smart sensors intelligence requirements (Section 3.5);
- The evaluation of knowledge management strategy: The proposed IoE Integrated Knowledge Management Model (Section 3.4).

This thesis approach consists in evaluating the maturity stages of KM strategy in IoE context, into a novel model, regarding knowledge management processes, self-governance, and self-learning of smart sensors, using interoperability communication capabilities.

The obtained maturity stages progression consists, therefore, of six sequential stages (communication capability of M2M, H2M, and H2H interactions) of sensors' ability to communicate and change information. This ability may vary at different levels of interoperability between IoE sensors and systems, and be classified as (0) no connection (no interoperability between enablers), (1) technical (basic connectivity and network connectivity), (2) syntactical (data exchange interoperability), (3) semantic (understanding in the meaning of the data), (4) pragmatic/dynamic (applicability of the information), or (5) conceptual (shared view of the world) (NOURA; ATIQUZZAMAN; GAEDKE, 2019). As shown in Table 5.

Table 5. Interoperability levels

Interoperability Level	Interoperability
(0) no connection	No connection between smart objects found in the physical world
(1) technical	Different networking protocols and technologies are used to provide networking interoperability in IoT.
(2) syntactical	Interoperation of the format and the data structure used in any exchanged information or service between heterogeneous IoT system entities.
(3) semantic	Different smart sensors, services, and applications exchange information, data, and knowledge in a meaningful way.
(4) dynamic	Extensive knowledge of a cross-platform IoT application platform, specific APIs, and information models of each different platform to adapt their applications from one platform to another.
(5) conceptual	Seamlessly cooperate and communicate with each other to realize the full potential of the IoT ecosystem.

The IoE Integrated Knowledge Management Model is presented in Figure 18.

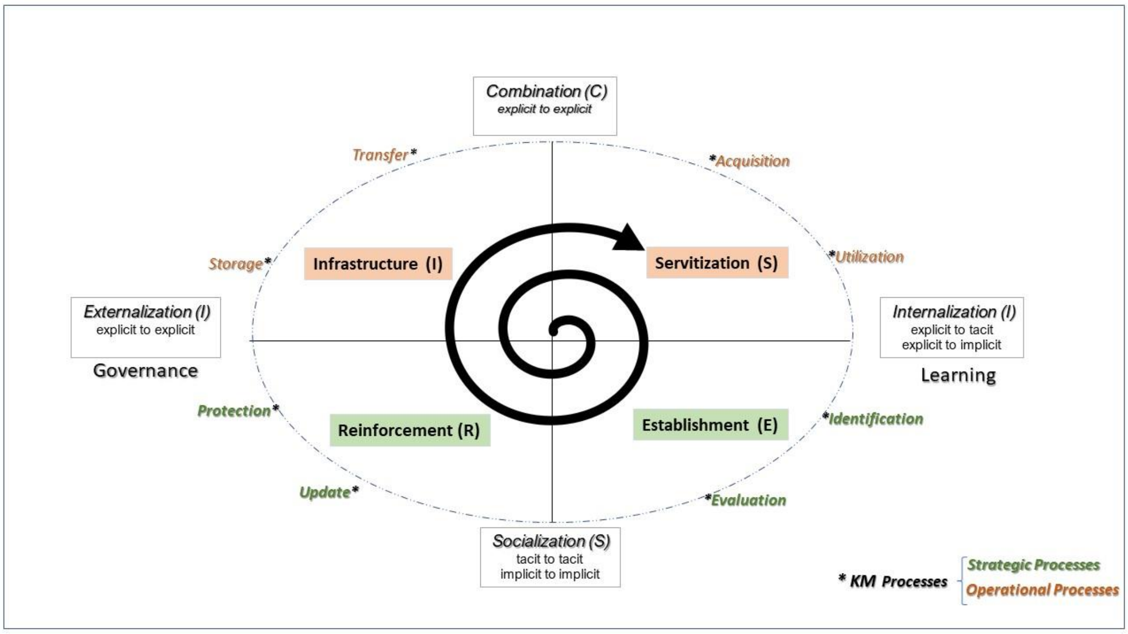


Figure 18. IoE Integrated Knowledge Management Model (prepared by the author)

Specifically, in IoE, knowledge creation is based on the conversion of tacit, explicit, and implicit knowledge of IoE enablers. When people bring knowledge and experience in some situations, they create, use and share tacit knowledge (SHARIQ; VENDELO, 2011). Explicit knowledge can be expressed and codified; implicit knowledge is defined as knowledge that is not explicit but derived from implicit information stored in a system ('wired in') (DAVIES, 2015). For Kamthan (KAMTHAN; FANCOTT, 2011), implicit and tacit dimensions represent types of internal knowledge that can be, but not has been, articulated (KAMTHAN; FANCOTT, 2011).

The knowledge-creation process is expressed by the SECI model (NONAKA; KONNO, 1998), consisting of four knowledge conversion processes: Socialization (S), Externalization (E), Combination (C), and Internalization (I) (NONAKA; KONNO, 1998)(NONAKA; TOYAMA, 2015). The flow through the four modes of knowledge conversion forms a spiral of knowledge creation. In IoE environments, the SECI model conceives knowledge creation as follow (EDWARDS, 2015):

- *Socialization*: IoE enablers share their knowledge of the IoE environment through collaboration and their practical consciousness and absorb knowledge through actions and perceptions of implicit knowledge in IoE applications (FARIAS DA COSTA; OLIVEIRA; DE SOUZA, 2021).

- *Externalization* occurs when tacit knowledge and/or implicit knowledge (data analytics) are made explicit to become the basis of new knowledge, to rationalize and articulate the IoE context surroundings.
- *Combination*: It consists of processing explicit knowledge to form more complex and systematic explicit knowledge from analytics capabilities and value creation for intelligent services.
- *Internalization* occurs when explicit knowledge is converted into tacit knowledge from human sensors combined with models from learning systems (implicit knowledge).

Kim (KIM, 2019) studied how services evolve and proposed a service operation model that expresses the evolution of services in a spiral trajectory, called the SERI cycle. The SERI cycle method (KIM, 2019) is defined in four evolution quadrants: Servitization (S), Establishment (E), Reinforcement (R), and Infrastructure (I).

Services have tangible (product-based and engineering domains) and intangible elements (human-based and knowledge domains). Usually, in a service centered on tangible elements, the cycle starts in the first quadrant, Servitization. On the other hand, when service is centered mainly on intangible elements, the cycle starts from the second quadrant, becoming the E-R-I-S cycle.

Table 6 presents the integration of SERI cycles with knowledge creation processes in the SECI Model and recommended activities related to KM processes.

This approach leverages awareness of intelligence sources in IoE applications, supports e-governance and meta-learning, aligned with a knowledge management strategy.

The development of a specific framework for knowledge management in IoE applications favors the evolution of knowledge management research in an IoE dynamic environment. As a theoretical background, the Hierarchical Model for Knowledge Management, proposed by Prat (PRAT, 2011) supports an effective conceptual representation of knowledge management from a strategic point of view.

These processes are facilitated by technological advances such as IoT, Big Data, data analytics, and services (*Services as Infrastructure*) and by collaboration between humans and machines (*Services as Interactions)*.

IoE Integrated Knowledge Management Model (IoE IKM Model) proposes integrating service science and knowledge management research to support governance of IoE applications for intelligence service evolution. It integrates knowledge conversion processes (SECI process) (NONAKA; KONNO, 1998) and service evolution cycles (SERI cycle) (KIM, 2019), to support the design of intelligent services centered around the process of creating knowledge and value in the IoE context. Specifically, the proposed model considers the flow and conversion of knowledge from sensors and actuators, humans and machines, human-machine collaboration, and the use of IoT and data analytics.

The evolution of products and services in a spiral trajectory, defined by (KIM, 2019) as the SERI cycle goes through four evolution quadrants: **Servitization** (S), **Establishment** (E), **Reinforcement** (R), and **Infrastructure** (I). Services have tangible (product-based and engineering domains) and intangible elements (human-based and knowledge domains). Usually, in a service centered on tangible elements, the cycle starts in the first quadrant, **Servitization**. On the other hand, when service is centered mainly on intangible elements, the cycle starts from the second quadrant, **Establishment**.

Table 6 presents the processes of service evolution positively related to knowledge management capabilities in the IoE context. The cyber-virtual environment in the IoE paradigm is the '*shared space*' in which knowledge is embedded, a platform for knowledge creation. Knowledge is created when people and machines interact and collaborate between themselves or with their environments (physical space or virtual space) in a shared time, energy, and place, defined by Nonaka *et al.* (NONAKA; KONNO, 1998) as *Ba*. And the IoE enablers (sensors and actuators) are 'k*nowledge assets*' (KA), resources specific to a domain application that can aid in the knowledge creation process and value creation. Knowledge Management processes are the strategies that link the three together, knowledge assets, knowledge conversion process, and the shared context for knowledge creation, *Ba* (NONAKA; KONNO, 1998).

3.4.1 First Quadrant: Servitization (S) and Serendipity

In this quadrant, the focus is service utilization (KIM, 2019). In this regard, intelligent service systems use the generated and collected data from smart products, the user, and the environment to create new and enhanced customer values (PAUKSTADT; STROBEL; EICKER, 2019).

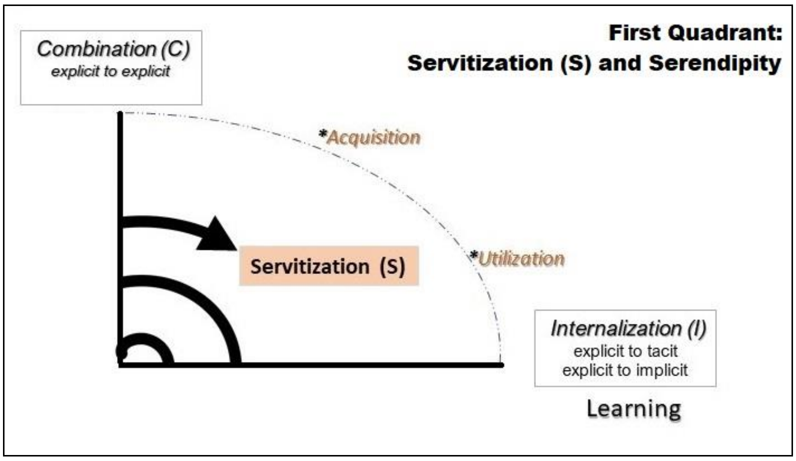


Figure 19. First Quadrant: Servitization (S) and Serendipity

Knowledge assets: IoE Enablers (tacit, implicit, or explicit knowledge)

Knowledge conversion process: The *Internalization* process (explicit-to-tacit, explicit-to-implicit conversion) consists of analyzing the explicit, classified, and organized data to make accurate decisions (AL-QURISHI *et al.*, 2015). It takes place in KMaaS on aggregated data such as lessons learned or codified knowledge leveraged from anywhere, anything, and anyone in a distributed computing environment (OCHS; RIEMANN, 2016). In M2M interactions, *Internalization* refers to self-learning.

Learning: Supported by Acquisition and Utilization (Knowledge Processes)

Knowledge Management Processes: Operational Processes

- **Acquisition Processes**: The combination of explicit knowledge in knowledge sources to support the use of a service or product based. Comprises all activities that increase the global stock of knowledge potentially useful to the IoE experience.
- **Utilization Process**: Consists in learning by doing, creating implicit knowledge (machine learning) or tacit knowledge from the user

experience (procedural knowledge). New ideas will come from meta-learning. Utilization is the application of knowledge.

Interoperability Maturity Assessment (IMA): Ability of IoE Enablers to exchange and use information during internalization (support self-learning) and combination of knowledge in H2H, M2H, and M2M interactions.

3.4.2 Second Quadrant: Establishment (E) and Evaluation

After identifying new opportunities for applying knowledge, it is important to socialize and focus on the collaboration of knowledge sources. And identification of new opportunities for value creation. Refers to the ability to learn with enhanced services and to identify innovation opportunities.

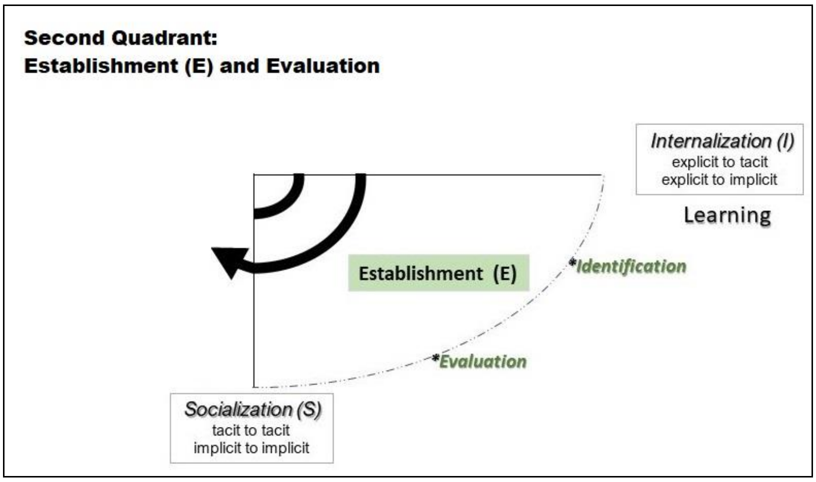


Figure 20. Second Quadrant: Establishment (E) and Evaluation

Knowledge assets: IoE Enablers (mainly intangible assets: tacit or implicit knowledge)

Knowledge conversion process: The *Socialization* process (tacit-to-tacit, implicit-to-implicit) conversion consists of sharing and managing valuable knowledge and sharing similar interests. When knowledge services involve, different fields and areas, the providers need to build a broad knowledge network (MA; SUN; SONG, 2015).

Services as interactions: M2M, P2M, and P2P are supported by shared knowledge through social, partners, or corporate networks (AL-QURISHI *et al.*, 2015). (Knowledge Processes)

Knowledge Management Processes: Strategic Processes

Identification and Evaluation: Then, self-innovation drives the process of satisfying new demands of consumers and providers where insights emerge from virtual, physical systems, and human knowledge involvement (DRAGICEVIC *et al.*, 2017).

- **Identification** consists of the identification, mapping, and modeling of current knowledge or of knowledge necessary to achieve previously defined objectives.
- **Evaluation**, which may be operated at various levels: the evaluation of knowledge, the evaluation of KM projects and/or of KM systems (KMSs) resulting from these projects, and the evaluation of KM.

Interoperability Maturity Assessment (IMA): Ability of IoE Enablers to exchange and use information during socialization (support knowledge sharing in P2P, M2P, and M2M interactions).

3.4.3 Third Quadrant: Reinforcement (R) and Governance

This phase comes from knowledge sharing and learning by doing from the previous quadrants. In this regard, intelligent products or services facilitate new data qualities, revealing hidden demands, customer actions, and resources to the service provider (PAUKSTADT; STROBEL; EICKER, 2019).

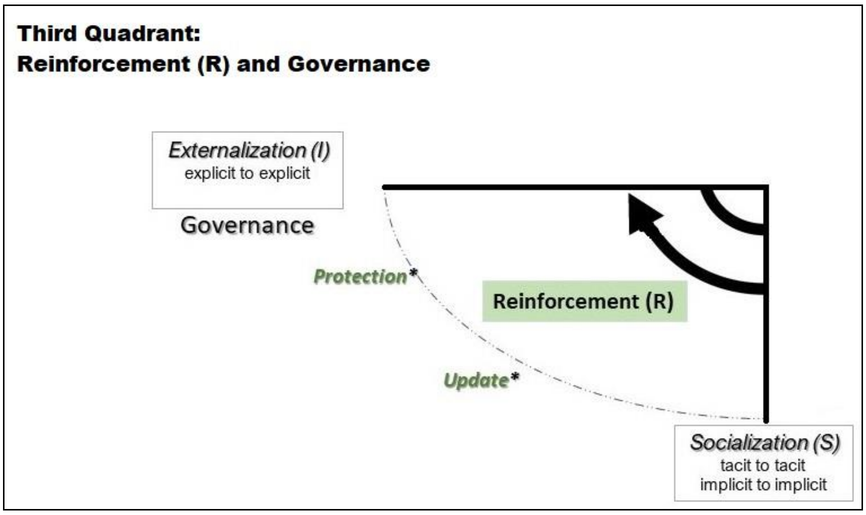


Figure 21. Third Quadrant: Reinforcement (R) and Governance

Knowledge assets: IoE Enablers (mainly tacit and explicit knowledge)

Knowledge conversion process: In this quadrant, the *Externalization* process (tacit-to-explicit knowledge conversion) emerges when service consumers access the knowledge acquired and convert it into concepts for the final use. In this scenario, final findings generate rules for improvements and adaptive changes in the environment (AL-QURISHI *et al.*, 2015).

Governance and control are supported by Update and Protect Knowledge Processes. This quadrant refers to reinforcement of what was identified as an opportunity in the previous phase.

Knowledge Management Processes: Strategic Processes

- **Update**: It consists of knowledge creation from the collaboration of knowledge sources and protection of knowledge through externalization or governance rules and regulations. Consists in enhanced services that strengthen intangible elements to meet the evolving demands of IoE's disruptive environment.
- **Protection**: The protection of knowledge through various means (patents, firewalls, etc.).

3.4.4 Fourth Quadrant: Infrastructure (I) and Technology

Refers to Knowledge Storage and Transfer. Drives the improvement of the service environment so that required resources are provided (MA; SUN; SONG, 2015) and enhanced intelligent services reinforced in the previous quadrants rely on awareness of IoE enablers and capabilities that foster new forms of value creation (PAUKSTADT; STROBEL; EICKER, 2019)(KIM, 2019).

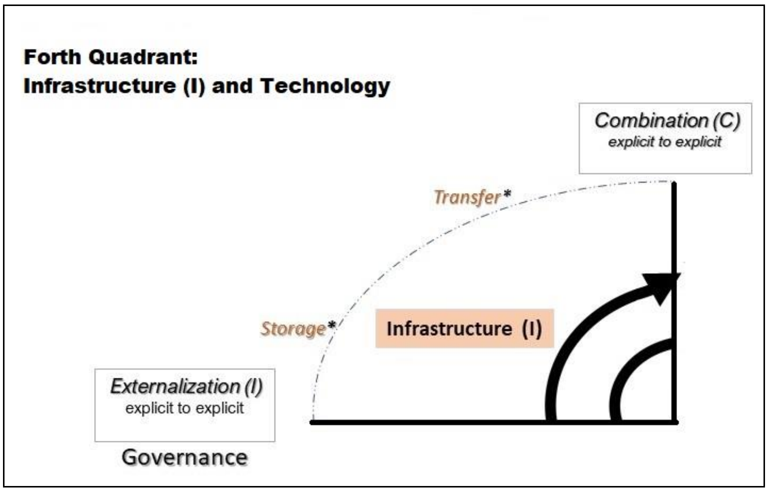


Figure 22. Forth Quadrant: Infrastructure (I) and Technology

Knowledge assets: IoE Enablers (mainly explicit knowledge)

Knowledge conversion process: The *combination* process (explicit-to-explicit knowledge conversion) finally occurs when explicit knowledge is captured, organized, indexed, classified, and stored to support the following evolving cycles (AL-QURISHI *et al.*, 2015).

Knowledge Management Processes: Operational Processes

Service as Infrastructure supports the infrastructure for product and service and refers to the storage and transfer of codified knowledge. It benefits from IoT technologies, analytics, and applications.

- **Storage** consists in retaining knowledge in individual or collective memory. Knowledge is indexed to facilitate future retrieval.
- **Transfer** is the sharing of knowledge between individuals, groups, and organizations.

Table 6. IoE Integrated Knowledge Management Model

<table>
<tr><th colspan="6">IoE Integrated Knowledge Management</th></tr>
<tr><th>Service Design</th><th colspan="5">Knowledge Management Strategy (KM)</th></tr>
<tr><th>Service Cycle Process</th><th>Knowledge Assets or Enablers</th><th>Knowledge Conversion Process</th><th>KM Processes</th><th>Interoperability Maturity Assessment (IMA)</th><th>Contextual recommended activities</th></tr>
<tr><td rowspan="2">Servitization (S)</td><td rowspan="2">Tacit
Implicit
Explicit</td><td rowspan="2">Combination
Internalization</td><td>Acquisition</td><td>The ability of IoE Enablers to exchange and use information
(0 – 5)</td><td>Analyze big data generated by IoT devices as a rich source of the user’s context.
Analyze generated social data to achieve collective intelligence (eg. using crowdsensing)
Maintain context-awareness of social relationships from users and devices.
Maintain context-awareness of infrastructure capabilities as well as information semantic perspective.
Supports contexts for individuals to internalize tacit knowledge using the explicit knowledge communicated through the IoE environment</td></tr>
<tr><td>Utilization.</td><td>The ability of IoE Enablers to exchange and use information
(0 – 5)</td><td>Offer personalized services and customized content according to the user’s social context.
Use of artificial social agents to generate and manage actionable social knowledge within the IoE environment.
Allow devices in the execution of automatic tasks without the involvement of the humans
Support collaboration and cooperation between IoE devices and interoperability of services on behalf of the humans.
Maintain context-awareness and record the resulting interactions and learn by doing.
Interact with big data tools and other analytical software to gain the experience</td></tr>
<tr><td rowspan="2">Establishment (E)</td><td rowspan="2">Tacit
Implicit
Explicit</td><td rowspan="2">Internalization
Socialization</td><td>Identification</td><td>The ability of IoE Enablers to exchange and use information
(0 – 5)</td><td>Support intelligence orchestration in M2H interactions
Understand the IoE contexts and customize services and applications accordingly.
Foster M2H interactions in a shared time, and place (physical or cyberspace)</td></tr>
<tr><td>Evaluation</td><td>The ability of IoE Enablers to exchange and use information
(0 – 5)</td><td>Maximize the system knowledge about the social dimension of the users.
Maximize context-awareness of knowledge in IoE applications, computational capability perspective as well as information semantic reasoning perspective. Evaluate Knowledge Sources, Knowledge Systems, and KM strategy for service evolution</td></tr>
</table>

<table>
<tr><th colspan="6">IoE Integrated Knowledge Management</th></tr>
<tr><th>Service Design</th><th colspan="5">Knowledge Management Strategy (KM)</th></tr>
<tr><th>Service Cycle Process</th><th>Knowledge Assets or Enablers</th><th>Knowledge Conversion Process</th><th>KM Processes</th><th>Interoperability Maturity Assessment (IMA)</th><th>Contextual recommended activities</th></tr>
<tr><td rowspan="2">Reinforcement (R)</td><td rowspan="2">Tacit
Implicit
Explicit</td><td rowspan="2">Socialization
Externalization</td><td>Update</td><td>The ability of IoE Enablers to exchange and use information
(0 – 5)</td><td>Support a live knowledge network, as the observed nodes' activities and profiles change over time due to IoE environment dynamics.
Develop machines’ thinking abilities side-by-side with their social integration abilities.
Maintain tight coupling of AI techniques merged with the humans' and machines' social context.
Cultivate a serendipitous environment through the collaboration of IoE devices.</td></tr>
<tr><td>Protection</td><td>The ability of IoE Enablers to exchange and use information
(0 – 5)</td><td>Evaluate the trust level of IoE nodes and applications and infer the reliability among devices.
Implement a social privacy preserving scheme to support trust.
Protect the social properties of users as sensitive information to support the customization of offered services.
Provide a knowledge protection strategy on behalf of critical knowledge identified for IoE applications.</td></tr>
<tr><td rowspan="2">Infrastructure (I)</td><td rowspan="2">Tacit
Implicit
Explicit</td><td rowspan="2">Externalization
Combination</td><td>Storage</td><td>The ability of IoE Enablers to exchange and use information
(0 – 5)</td><td>Support data management activities at the unit IoT level, involving pre-processing and filtering tasks, such as data aggregation and data compression.
Support data acquisition for the local unit IoT and complements it with external data such as open linked data and knowledge graphs or codified knowledge from data sources</td></tr>
<tr><td>Transfer</td><td>The ability of IoE Enablers to exchange and use information
(0 – 5)</td><td>Use social networks to solve IoT-related issues related to the scalability of interconnected objects.
Support service recommendation system to leverage the social relationships between IoT devices’ owners. Support a socially connected community of sensors and actuators
Integrate communication and processing technologies near end-user devices
Improve the network performance, reducing unnecessary network traffic and increasing the throughput while replying to the users’ requests.
Provide state-of-the-art technologies, software, databases, and repositories</td></tr>
</table>

3.5 How Smart is a Sensor? Smartness requirements for IoE

Smartness is a broad concept related to what extent smart sensors contributes to IoE value creation and it is derived from knowledge transformations or related to the experience of using sensors and actuators, sometimes related to observation facilities and the support for monitoring and control solutions in the evolution of IoT paradigm.

This Section will present smartness requirements for sensors and actuators towards intelligent services goals in IoE applications. IoT devices have an important role in realizing the IoE paradigm, thus it is vital to consider their capabilities in addressing interoperability and providing intelligence services for IoE applications (NOURA; ATIQUZZAMAN; GAEDKE, 2019). Therefore, the main research question of this work proposal is formulated as "How do smart sensors contribute to the Quality of Intelligent Services in IoE applications?" There is a challenging need to satisfy the quality of intelligent services (QoS) requirements in distinct domains of IoE applications.

Internet of Things (IoT) is seamlessly connecting the real world and the virtual world using intelligent sensors smarter than before empowering users to salvage vital information which in turn will help in decision making (YU *et al.*, 2017) (SINGH; SINGH TOMAR, 2019).

Kolar (KOLAR; BENAVIDEZ; JAMSHIDI, 2020) described significant challenges for decision-making due to the safety, efficiency, and accuracy requirements. For reliable operation, decisions on the system need to be made by considering the entire set of multi-modal sensor data, keeping in mind a complete solution.

However, there is a lack of a review and discussion on ranking smart sensors intelligence in IoE, as well as the emerging challenges and new issues in knowledge management applied to this field of research.

To understand the latest trends in studies on smart sensors and what's the focus of intelligence in IoE applications and related works on smart sensors, a systematic literature review was conducted on digital libraries. The methodological guidelines suggested by Kitchenham and Charters (KITCHENHAM *et al.*, 2010) for literature reviews guided this survey. The review included contributions from the ACM Digital Library, IEEE Digital Library, ISI Web of Science, Science@Direct, and Scopus databases, which were the most relevant for finding specific studies in journal and conference papers in English. The specific search string was sought: "intelligent sensor" OR "smart sensor" in the "Abstract" fields.

The search string was designed to retrieve from the databases as many studies as possible that were relevant to the review, even if the query results returned articles not relevant to the survey. Relevant studies not retrieved after the first query were also included in a second iteration analysis in December 2021, considering studies likely to be explicitly related to smart sensors in IoT or IoE applications. Furthermore, most contributions were related to the application of smart sensors for IoT, which indicates a lack of maturity in work in the field of IoE.

Only studies published in English in journals (already published and in press), conference proceedings, books, and technical reports were selected. After discarding the duplicates, a total of 130 candidate articles remained from the initial search (Table 7).

Table 7. Summary of "smart sensors" literature review stages

Literature review stage	number of papers
Search of ISI Web of Science	81
Search of Scopus	576
Search of IEEE	262
Search of ACM Digital Library	16
Science@Direct	8
Total	**943**
Duplicates	128
Total after discarding duplicates	815
Approval for analytical reading	**130**
Discarded	685

A total of 130 related articles were collected and analyzed based on their title, keywords, and abstracts. Among these documents, the most influential and highly cited articles are selected and discussed. The findings would assist researchers in understanding current developments and barriers in the IoE systems adoption. Although Table 7 presents fruitful work and progress, this research domain still confronts challenges on theories and practice.

This work identified distinct approaches of smart sensor and applications which have been applied to IoE Applications in multi-domains. The studies were categorized in terms of IoE Knowledge-based Taxonomy categories. Table 8 shows this categorization of smart sensors works according to the identified requirements to which they have been focused and knowledge goals they support.

As aforementioned in Section 2.2, ranking knowledge in IoE sensors is a composition of characteristics in IoE applications knowledge sources regarding the kind of knowledge they provide, the type of sensor itself, the observation within ever-changing contexts, and the technological capabilities of sensors, as presented in Table 8. The selected requirements were grouped related to what extent it provides smartness to each category of IoE Enablers proposed by (FARIAS DA COSTA; OLIVEIRA; DE SOUZA, 2021) in IoE Knowledge-based Taxonomy. This methodology addresses the challenge imposed due to distinct applications of smart sensors in the IoE domain.

To support the multidisciplinary vision proposed in this work, smart sensors requirements were derived from the literature review to represent the intelligence in IoE applications. Each identified requirement was related to a category of IoE enablers, which defines the challenges to smart sensors in support of IoE in each of the categories (knowledge, type of sensors, observation capability, or technology).

Aiming to identify those different requirements that characterize this multidisciplinary of what to consider smartness in IoE solutions, recent works were analyzed the recent works identified in the SLR with challenges and benefits of smart sensors and actuators in IoE applications. The analysis was based on IoE knowledge-based taxonomy categories and leads us to propose the 18 smartness requirements, supporting each IoE category. The proposed requirements were organized in Table 8 assigned to related works. The taxonomy shows the categorization of the works according to the type of problems to which they have been applied, some goals have been applied to more than one type of problem, and hence, they appear more than once in the taxonomy. The challenge of sensors smartness in IoE applications will be translated into smartness requirements according to specific goals:

3.5.1 Related to Knowledge goal

The initial step is raw data capture using smart sensors, the challenge they try to solve is mapping the multiple streams of raw sensory data to related distinct and conflicting tasks, which complicated the problem. This resulted in system learning to translate the multiple inputs to the appropriate tasks or sequence of system actions. Combining data sources (sensor input and output values) in a cooperative environment is summarized as follows (KOLAR; BENAVIDEZ; JAMSHIDI, 2020):

- Data-in-data-out (DAI-DAO): Raw data are input and raw data are extracted out;

- Data-in-feature-out (DAI-FEO): Raw data are sourced, but the system provides features as output.

- Feature-in-feature-out (FEI-FEO), also called feature-fusion: Features or processes from previous steps of fusion are fed into the fusion system and better features or higher-level features are output.

- Feature-in-decision-out (FEI-DEO): The features are input to provide decisions for tasks and goals as output.

- Decision-in-decision-out (DEI-DEO): Lower-level decisions are accepted by input and higher-level better decisions are processed out.

IoT sensors are efficiently used in various IoT applications for creating a smart environment (SEHRAWAT; GILL, 2019). For instance, Alahi and Mukhopadhyay (ALAHI; MUKHOPADHYAY, 2019) discussed IoT-enabled smart sensors and sensing systems that were developed to measure nitrate concentration in water. Regular measurement of nitrate is critical to keep the water safe for all purposes. The sensing system can be installed at any sampling location, and the system can measure the nitrate concentration and transfer it to the cloud server for further analysis. Advances in the Internet of Things (IoT) applications resulted in emergence of smart contexts, governed by real-time monitoring with smart sensors embedded and analytics.

The combination of the Internet of Things (IoT) and the blockchain paradigms helps in the development of automated and trusted systems. Aligned to this concept, Ahmed *et al.* (AHMED *et al.*, 2021) presented a logistic traceability smart contract developed on top of a blockchain (AHMED *et al.*, 2021).

So smart sensors should be seamlessly, securely, and trustworthy interconnected to enable automated high-level smart applications (DATTA; SHARMA, 2017).

Focusing on collaboration to support intelligent services, Poza-Lujan *et al.* (POZA-LUJAN *et al.*, 2020) proposed an architecture to recognize heterogeneous smart sensors, which are called smart resources in intelligent environments. Smart resources process local sensor data and offer information to other devices as a service. These resources can be in the same operating range (the edge), in the same Intranet (the fog), or on the Internet (the cloud). As requisite, smart resources must have an intelligent layer to process the information and capabilities to collaborate closely with other devices.

For Gomba and Nleya (GOMBA; NLEYA, 2018) the emergence of the Internet of Things (IoT) benefit mankind via physical objects embedded with intelligent sensors of varying types, in support of intelligent decision making, as well as be provisioned of beneficial services. The basic premise is to have smart sensors collaborate directly without human involvement to deliver a new class of applications (JIENAN; XIANGNING; SHUAI, 2021).

For Voicu *et al.* (VOICU; PETREUS; ETZ, 2020), the Internet of Things (IoT) is now beginning to witness the maturity technology level. Blockchain (KHRAIS, 2020) is an emerging technology considered an ideal candidate to counter the flaws of IoT, among which there is security. A blockchain network is deployed to mitigate the native vulnerabilities of IoT and to ensure that data collected is decentralized, accessible, transparent, lightweight, and scalable. Roman and Ordieres-Mere (ROMAN; ORDIERES-MERE, 2019) applied smart sensors in IoT system that collects, send, store, and publishes relevant data in a blockchain-like database, and publish a temporal statistic data summary.

For Haldorai *et al.* (HALDORAI; RAMU; SURIYA, 2020), authentication remains to be the vital security element in IoTs applications. Machine-learning (ML)-based remedies mitigates various security problems such as accessibility and authentication controls in IoTs. Solangi *et al.* (SOLANGI *et al.*, 2018) revealed a holistic approach of device identification, authentication, management, security, and privacy concerns for a global, immersive, invisible, ambient network-computing environment built through the continued proliferation of smart sensors.

This thesis proposes the following requirements for smart sensors regarding knowledge goals to support smart services in IoE applications.

3.5.1.1 Effectivity

Effectivity is the main noun form of the adjective effective ("EFFECTIVE | Meaning & Definition for UK English | Lexico.com", 2022), which means "*adequate to accomplish a purpose; producing the intended or expected result*". More than sensing the environment smart sensors or smart nodes extract meaningful knowledge from the data through machine learning technologies (CHEN *et al.*, 2020) and collaborate directly without human involvement to deliver a new class of applications (JIENAN; XIANGNING; SHUAI, 2021). The intelligence (SONG *et al.*, 2019) and smartness of smart sensors are related to applications purpose and criticality (KORONIOTIS *et al.*, 2020) and proportional to its extent for empowering users in decision making (YU *et al.*, 2017) (SINGH; SINGH TOMAR, 2019) or in cyber-physical experiences for expecting outcomes.

3.5.1.2 Interpretability

The challenge is raw data capture using smart sensors, mapping the multiple streams of raw sensory data and enabling new ways to analyze data, combining data sources (sensor input and output values) in a cooperative environment (KOLAR; BENAVIDEZ; JAMSHIDI, 2020), and gain actionable insights (GUPTA, 2021). In (YIN; WANG; JHA, 2018) a hierarchical inference model has been applied for IoT applications based on hierarchical learning and local inferences to learn from these data to make things more intelligent.

3.5.1.3 Integrity

Integrity is a significant requirement in IoE applications, due to the outliers in sensor data, the integrity of the data source is not maintained, and data becomes inconsistent. This inconsistency is not acceptable in the transmission of data from sender to receiver (PUNDIR; SANDHU, 2021). In the field of data quality and integrity of information, ontologies will play an essential role in interlinked IoT systems (HONTI; ABONYI, 2019). Smart sensors generate smart data which should be semantically enriched to provide intelligent services in IoE applications. So smart sensors intelligence is derived from data (TENG *et al.*, 2019). And data collected from

IoT data sources need to be restricted controlled due to the limited capacity of these sources to ensure the security and the quality of their data (AHMED *et al.*, 2021).

3.5.1.4 Accuracy

Significant challenges for decision-making supported by IoE systems are due to safety, efficiency, and accuracy requirements (KOLAR; BENAVIDEZ; JAMSHIDI, 2020). Continued proliferation of smart sensors, decisions on IoE systems needs to be made by considering the entire set of multi-modal sensor data, keeping in mind a complete solution. To address traceability challenges, (WANG *et al.*, 2020) presents a logistic traceability smart contract solution (AHMED *et al.*, 2021) using blockchain technologies (KHRAIS, 2020). In Hama and Nepal's (HAMAD *et al.*, 2019) solution, a fingerprint was created for each IoE device. Broadly, Solangi *et al.* (SOLANGI *et al.*, 2018) revealed a holistic approach of device identification, authentication, management, security, and privacy for smart sensors in IoT.

3.5.1.5 Security

In the field of security in IoE applications, a reliability-driven design process is a focus. Major challenges are the design and development of security and privacy management schemes for IoT smart sensors with good performance, low power consumption, robustness to attacks, tampering of data, and end-to-end security (YAMINI; GANAPATHY, 2021).

For Pal et al (PAL *et al.*, 2020), the state of the art is lacking a systematic analysis of the security requirements for the IoT and presented security requirements for the IoT, which will help design secure future IoT systems by achieving much of the promised benefits of scalability, usability, connectivity, and flexibility practically and comprehensively.

Researchers have already studied the combination of IoT and Blockchain (especially smart contract) technology (HUANG; ZHANG; JIN, 2021). A smart contract, residing on blockchain technology, is defined in digital form, including agreements on which contract participants can execute these commitments.

3.5.2 Related to Sensor Characteristics goal

Sensor engineering is rooted in material choice, and the development of practical protocols that enhance device accuracy without sacrificing temporal resolution (GIL *et al.*, 2016). Smart sensors material choice dictates classification of the device as a regular sensor (use of abiotic materials), biosensor (biological or biomimetic materials), nano sensor (nanomaterials), or nano biosensor (hybrid nano/biomaterials). It is related to sensor critical performance factors such as durability, cost, and ultimately the quality of service (MCLAMORE *et al.*, 2019).

Ruppert *et al.* (RUPPERT *et al.*, 2018) present the concept of intelligent space, where the fast development of smart sensors and wearable devices has provided the opportunity to develop intelligent operator workspaces. But a variety of new challenges is emerging, with multiple parameters requiring control and intelligence (FRENCH; BENAKIS; MARIN-REYES, 2018).

New contexts that emerge daily in consequence of the dynamics of the real world eventually demand the development of new sensor types (ROZSA *et al.*, 2016). Sensors are pervasive solutions creating interactions between users and the environment anytime and anywhere (STEFANA *et al.*, 2021). Before design considerations which are based on material choice, the smart sensors are based on the recognition-transduction-acquisition (RTA) triad. The importance of this first step in the RTA triad cannot be over-emphasized,

transduction is the platform for innovation (MCLAMORE *et al.*, 2019). Two major classes of transduction that lead to the evolution of quantitative data or qualitative data, namely inherent transduction and engineered transduction, respectively are presented as follow (MCLAMORE *et al.*, 2019):

- In engineered transduction, the sensor cannot autonomously produce a measurable product. It depends on an engineered process or exogenous reagent (MCLAMORE *et al.*, 2019).
- In inherent transduction, sensors autonomously produce quantitative data (MCLAMORE *et al.*, 2019).

Stefana *et al.* (STEFANA *et al.*, 2021) provided an overview of the state of the art of smart wearables to support the selection of the most suitable smart sensors in industrial and non-industrial applications in IoE settings. The generation of creative solutions depends on the ability of the IoT designers and the context of the problem they intend to solve. Yang and Wei (YANG; WEI, 2019) address the problems in user-device interaction. Petrariu *et al.* (PETRARIU; COCA; LAVRIC, 2021) presented the design of a fully reconfigurable wireless sensor node that can sense the smart grid environment. The proposed solution is called “multi-sensor” due to the use of different sensors for data acquisition, such as temperature, humidity, air pressure, or ozone concentration, that are integrated into a modular hardware platform, attached throughout the network with self-monitor capabilities.

For Malík and Krištofík (MALÍK; KRIŠTOFÍK, 2020) the use of neural networks in mobile and IoT applications depends on special design techniques which would make them suitable for mobile or IoT applications with limited computational power (MCLAMORE *et al.*, 2019). The emergence of microsensors (very small size, weight, as well as low energy usage) within intelligent sensor framework technology permits the forefront production of a sensor framework (SHARMA; KAUR; YADAV, 2021).

Adaptability, integration, and usability are the focus when considering smart sensors design. Different insights about different applications and communication systems are provided in (RAMÍREZ-MORENO *et al.*, 2021a, 2021b), as smarter communities are those that can adapt through transparent and inclusive community engagement in the use of technologies based on local and regional societal needs and values.

3.5.2.1 Adaptability

Adaptability challenge is a consequence of the dynamics of the real-cyber physical world that demands the development of new sensor types: smart sensors with a special design that would be suitable for mobile or IoT applications with limited computational power (MCLAMORE *et al.*, 2019). Smart sensors applied in context-aware systems change the parameters of the environment or their own, gather information, and transmit it to other devices (ZHILENKOV *et al.*, 2017). Different challenges are the intelligent combination of multi-agent systems (to simulate collective behaviors of the smart sensors), knowledge graphs (to support communication among different devices), and deep learning architectures to create models from distinct sensor-based data (PETRARIU; COCA; LAVRIC, 2021).

3.5.2.2 Usability

In the field of smart sensor engineering, the challenge is in material choice, and the development of practical protocols that enhance device accuracy without sacrificing temporal resolution (GIL *et al.*, 2016). The sensor's smartness is related to its benefit in support of intelligent decision making, via physical objects of varying types (GOMBA; NLEYA, 2018). The emergence of intelligent microsensors (very small size, weight, as well as low energy usage) permits the forefront production of intelligence derived from data (SHARMA; KAUR; YADAV, 2021). For Rana and Bo (RANA; BO, 2020), friendly smart cyber-physical system design is the main challenge for IoT implementation. Moreover, the authors suggested the following requirements for the IoT communication systems regarding sensors and actuators: privacy, security, intelligent design, low cost and complexity, universal antenna design.

3.5.2.3 Durability

Still, in the field of smart sensors engineering, material choices are also related to sensor critical performance factors such as durability, cost, and ultimately the quality of service (MCLAMORE *et al.*, 2019). The aim is to integrate a low-cost and scalable network of smart sensors capable of mapping large areas in real-time (CABRA *et al.*, 2018).

3.5.3 Related to Observation goal

This category refers to technologies for sensing the environment and sensing context.

Advances in sensor technology, IoT, and machine learning methods, have turned recent environment monitoring into a smart environment monitoring (SEM) system (ULLO; SINHA, 2020), with the advances in the development of modern sensors. Mourtzis *et al.* (MOURTZIS; MILAS; VLACHOU, 2018) proposed a monitoring system for shop-floor control following the IoT paradigm consisting of a data acquisition device capable of capturing quickly and efficiently the data from the machine tools and transmits these data to a cloud gateway via a wireless sensor topology.

The development of sensor technology, processing techniques, and communication systems give rise to the development of the smart sensor for adaptive and innovative applications (SHIT *et al.,* 2018). As the number of sensors increases, the data handled by the network also increases significantly (MAHAKALKAR *et al.*, 2019).

Some works present the benefit of reducing the number of nodes (SINGLA; BOSE, 2018) or defining the point of monitoring interest. The work of Singla and Bose (SINGLA; BOSE, 2018) proposed a system to infer the user context from input data from various devices classifying points of interest (POI) to make sense of the input sensor data.

Yeh et Lin (YEH; LIN, 2018) presented a cooperative parallel simplified swarm algorithm (pSSO) to solve the redundancy allocation problem in IoT. The authors argue that it is the safest, most convenient, and most economical way to increase the reliability of smart sensor systems. Meeradevi *et al.* (MEERADEVI; MUNDADA; SANJAYKUMAR, 2018) presented a framework based on embedded intelligent sensor nodes with suitable embedded architecture for various multi-sensor applications.

Quek *et al.* (QUEK; WOO; LOGENTHIRAN, 2017)refer to intelligence injection where it is possible to detect multiple loads and states related to a single sensor, eliminating the need to have intelligence and communication features for every appliance. When the number of nodes is very high, as in large networks, it is very difficult to recharge, and sometimes the solution is some nodes replacement. Wason *et al.* (WASON; KUMAR; JOHRI, 2021) proposes a system with a limited number of sensors kept in an active state. But the system will constantly sense the changes around the active nodes and after detecting an intrusive change, a signal will be sent to other remaining nodes to turn themself into active states.

Purri *et al.* (PURRI *et al.*, 2017) refer to recent improvements in RFID with device-to-device advancements, to permit smart sensors and actuators to be detected and controlled remotely crosswise over the Internet of Things.

3.5.3.1 Mobility

Mobility of customized/personalized smart sensors allows the integration of a high-density smart sensors network distributed over a large-scale geographical area in real-time. Mobility of customized/personalized sensors allows the integration of a high-density of sensors distributed over a large-scale geographical area. This is possible by using LPWAN (Low-Power Wide-Area Network) technologies, due to its numerous advantages such as unlicensed spectrum transmitting, easy deployment by any hardware/software developer for both components, nodes, and gateways (MCLAMORE *et al.*, 2019). Xu and Chen (XU *et al.*, 2018) proposed a federated capability-based access control (FedCAC) framework to enable effective access control processes to devices, services, and information in large-scale IoT systems through delegating centralized authorization decision-making policy to local domain delegators.

3.5.3.2 Availability

Availability is a significant parameter of QoS and guarantees authorized users access to resources and information when required (PUNDIR; SANDHU, 2021). Some challenges of availability in IoT systems are a limited number of smart sensors inactive state (WASON; KUMAR; JOHRI, 2021), the ability to sense the changes around the active nodes after detecting a perceived change, or sending it to other remaining nodes to turn themself to the active state (PURRI *et al.*, 2017). In Chen and Khan (CHEN *et al.*, 2020) algorithmic design, computational optimization, and hardware revolution are promising solutions. In this sense, smart sensors integrate several detection methods, real-time data analysis, and connectivity.

3.5.3.3 Scalability

For Pundir (PUNDIR; SANDHU, 2021), a scalable network should perform well even when the count of extra nodes is increased after the designing of the network and can accommodate extra nodes at a later stage and improve its coverage. The region of interest is said to be fully covered if each location is monitored by at least one sensor node. Good coverage can be referred to how well sensors monitor a particular event and refer to monitorability. Smart sensor architecture incorporates real-time operation features, local data analysis, scalable big-sensing-data cleaning, scalable big-sensing-data compression, and cloud-based data curation with high availability communication interfaces, interoperability, and cyber-security (YANG *et al.*, 2021).

3.5.3.4 Monitorability

In the field of environmental monitoring and control, smart sensors intelligently perceive inputs from the environment, with secure and energy-efficient data collection (OSIFEKO; HANCKE; ABU-MAHFOUZ, 2020). In (KAMIENSKI *et al.*, 2018). Monitorability comes from context-aware systems able to adapt behavior automatically to instant environment conditions. Smart sensors are those which fundamentally change the way cyber and physical infrastructure systems are monitored, controlled, and maintained (PRUTEANU; GABRIEL, 2019). In Poza-Lujan *et al.* (POZA-LUJAN *et al.*, 2020), heterogeneous smart sensors are considered smart resources in intelligent environments. Smart resources can process local sensor data and offer information to other devices as a service.

Hammoudi *et al.* (HAMMOUDI; ALIOUAT; HAROUS, 2018) proposes the use of Infrastructure as a Service (IaaS) to support any IoE system where a huge data is generated and processed in real-time and uses sensory and social data such as traffic monitoring system, a health system, and other smart city domains monitoring systems.

3.5.4 Related to Capabilities goal

In IoT, smart sensors data creates challenges concerning storage and analytics given the resource constraints of these smart devices (KAUR *et al.*, 2017). Additionally, the large volume of information processed in cloud-based infrastructure may lead to long response times and higher bandwidth consumption. In this sense, edge computing, promises to support data processing and service availability at the edge of the network.

Smart sensors are based on built-in microprocessors and wireless communications, which fundamentally change the way civilian infrastructure systems are monitored, controlled, and maintained (PRUTEANU; GABRIEL, 2019).

For Yu, *et al.* (YU *et al.*, 2017) edge computing as a strategy is the solution to mitigate the escalation in resource congestion and to improve the performance of IoT networks, emerged as a new paradigm to solve IoT and localized computing needs to the network 'edge,' near the end-users. The advantages of this strategy in comparison with traditional cloud services are to offload the computational demands away from the centralized data center, and benefits in communication, in IoT networks reducing the latency avoiding the traffic peaks in information exchange processes and reducing response times for real-time IoT applications. Furthermore, the focus is broader than bandwidth occupation. Energy consumption and overhead are critical aspects that should be addressed. By transferring computation and communication overhead from nodes with limited battery supply to nodes with significant power resources to the system that can extend the lifetime of the individual nodes.

The explosion in the development and adoption of smart wearable sensors is demanding for specific infrastructure supporting real-time data analysis for anomaly detection, event identification, situation awareness as data produced by wearable sensors continuously grow, yielding to a sensor big data approach (GRECO; RITROVATO; XHAFA, 2019). Greco *et al.* (GRECO; RITROVATO; XHAFA, 2019) proposed a technological and architectural solution, composed of four distinct layers: a sensing layer, a pre-processing layer, a cluster processing layer, and a persistence layer to perform real-time analysis of wearable sensor data streams. The solution evaluates the performance of each layer considering CPU and memory usage.

To support IoT infrastructure, sensors will be placed on all manner of locations, and sometimes in inaccessible areas. In these areas, sensors work for a long time, so sensors design capabilities are looking forward to continuous delivery and self-maintaining devices. The power supply is a bottleneck of the sensor technology and using a battery as a power source will be unable to fulfill the requirements of the IoT (WU; CHENG; WANG, 2020). In this context, potential energy sources are solar, thermal, wind, chemical, mechanical, biomass, and so on. Wu *et al.* (WU; CHENG; WANG, 2020) defines two meanings for the term “self-powered sensor”: first, it is a sensor that automatically sends an electric signal when mechanically demanded without an external power source. Second, the operation power supply provided for the sensor is self-generated.

Cabra *et al.* (CABRA *et al.*, 2018) provided insights into the technologies that compose the IoT architecture to integrate a low-cost and scalable network of smart sensors capable of mapping large areas in real-time.

For Maiti *et al.* (MAITI *et al.*, 2018), cloud-IoT solutions focused on centralized data collection and storage are not appropriate for efficient data collection and utilization for sensor data processing and fast real-time decision making. For addressing IoE/IoT's diverse set of requirements, resources should be placed near the data sources instead of sending all the data to the cloud. The results showed a total energy saving and reduction in latency compared to processing IoT data in a conventional cloud system.

Intelligent sensors and actuators support the linkage of computation and interoperability (YANG *et al.*, 2021). Bansal and Kumar (BANSAL; KUMAR, 2020) provide a technical overview of IoT enabling architectures, devices, gateways, operating systems (OS), middleware, platforms, data storage, security, communication protocols, and interfaces in an overview of the taxonomy of the IoT ecosystem.

Kurniabudi *et al.* (KURNIABUDI *et al.*, 2018) presented a global framework for anomaly detection in IoT and proposes a distributed preprocessing framework to overcome the challenge in data preprocessing and analysis of huge and heterogeneous data on smart sensors in IoT.

Chanal and Kakkasageri (CHANAL; KAKKASAGERI, 2020) studied the design and development of security and privacy management schemes for IoT smart sensors. The objective factors are good performance, low power consumption, robustness to attacks, tampering of the data, and end-to-end security.

For Abbas *et al.* (ABBAS; PRIYA, 2019), the controlling part of the connected sensor devices and communication devices are crucial, the main purpose of their work is to design a smart sensor controller that provides reliable data transmission between process controller and sensor node by using critical communication and massive IoT solution.

Silvestre-Blanes *et al.* (SILVESTRE-BLANES; SEMPERE-PAYÁ; ALBERO-ALBERO, 2020) presents a method called Interactive to determine the operating parameters of the dynamic governor algorithm which offers significant improvements in power consumption, without reducing the performance of the application.

Data collaboration is where a cloud server instructs smart sensor nodes on the edge of the network to perform specific aspects of a data processing task, such as filtering, denoising, filing, combining data, and so on. It improves data processing power and focuses on reducing latency and providing highly customizable computationally intensive data processing services (SUN *et al.*, 2021).

3.5.4.1 Communication efficiency

IoT world of smart sensors demands the popularity of lightweight and simple methods to implement communication protocols among humans, machines, and sensors (SILVA *et al.*, 2019). The edge computing concept allows the distribution of intelligence and the use of intelligent sensors.

The rapid development of smart sensors in different applications imposes challenges in optimizing the QoS in terms of performance, privacy, and security levels to satisfy the QoS requirements due to the dynamic network condition, heterogeneous traffic flows, and resource-constrained behavior of sensor nodes (PUNDIR; SANDHU, 2021).

3.5.4.2 Processing efficiency

In this field, the challenge is the optimal merging of complex distributed computing environments technologies with smart sensors with additional computational capabilities (YANG *et al.*, 2017) (YU *et al.*, 2017). Some works address the challenge in data preprocessing and analysis of huge and heterogeneous data on smart sensors on the Internet of Things (KURNIABUDI *et al.*, 2018) (LAMMEL *et al.*, 2021).

In this sense, Markiewicz *et al.* (MARKIEWICZ *et al.*, 2019) propose a novel architecture for IoT, in which a sensor processes data locally thanks to a decrease of computational complexity given by the usage of compressed recurrent neural networks. Local processing of the data on ultra-low power wireless sensors gives comparable outcomes in terms of accuracy but much better results in terms of energy consumption than transferring the raw data.

Edge computing as a strategy brings benefits in communication, in IoT networks, reducing the latency and avoiding the traffic peaks in information exchange processes, and reducing response times for real-time IoT applications.

3.5.4.3 Storage Efficiency

Considering challenges concerning storage, smart sensors are due to storage and analytics resource constraints (KAUR *et al.*, 2017). To address IoE/IoT set of requirements, resources are placed near to the data sources instead of sending all the data to the Cloud, so (KAUR *et al.*, 2017) smart sensors support data processing and service availability at the edge of the network, as the large volume of information processed in cloud-based infrastructure may lead to long response time and higher bandwidth consumption. In Hammoudi *et al.* (HAMMOUDI; ALIOUAT; HAROUS, 2018), their approach provides intelligent data storage to minimize the latency of any input and output data requests in a massive data storage and a huge number of servers, in an Infrastructure as a Service (IaaS) approach.

3.5.4.4 Energy efficiency

In the energy engineering field, the challenge is smart, secure, and energy-efficient data collection processes. The power supply is a bottleneck of the sensor technology (WU; CHENG; WANG, 2020). In this context, smart sensors use potential energy sources such as: solar, thermal, wind, chemical, mechanical, biomass (WU; CHENG; WANG, 2020) to be “self-powered sensors”(SILVESTRE-BLANES; SEMPERE-PAYÁ; ALBERO-ALBERO, 2020). For (YU *et al.*, 2017), energy consumption is a critical aspect that should be addressed in IoE/IoT systems (OSIFEKO; HANCKE; ABU-MAHFOUZ, 2020). Energy-efficient data collection (DC) processes are key to the realization of the full potentials of future Internet of Things (FIoT)-based systems. For (AKMANDOR; YIN; JHA, 2018), edge-side computing and cryptographic techniques have been proposed to get around limited bandwidth, insufficient energy, and security concerns of the use of cloud resources, as a result of increased computational load and energy consumption, it is difficult to simultaneously achieve smartness, security, and energy efficiency.

Lammel *et al.* (LAMMEL *et al.*, 2021) developed specialized architectures for smart sensor systems, focusing on close hardware/software co-design, to achieve ultra-low power consumption in the execution of high-performance algorithms, while staying flexible in programming.

3.5.4.5 Maintainability (low cost, low complexity)

Pundir (PUNDIR; SANDHU, 2021) defined Maintainability as "*the probability of performing a successful repair action within a given specific time*". As smart sensors operations last for a long and uninterrupted period, are placed in all manner of locations, and sometimes in inaccessible areas. sensors design capabilities are looking forward to continuous delivery and self-maintaining devices (MALDONADO *et al.*, 2018). Smart sensor requirements relate to their optimization in cost, size, and power requirements (MALDONADO *et al.*, 2018). For Rusnack (RUSNACK, 2021), the evolution of sensing technology has resulted in increasingly more affordable smart sensors with low-cost integrated electronics and inexpensive microcontrollers with integrated data conversion technologies.

Table 8. Proposed Smart Requirements for IoE Applications

Sensors Requirements	**IoE Category supported**	**Related Works**
Effectivity	Knowledge (What)	(JANEERA *et al.*, 2021) (KULKARNI; VANI; HUNAGUND, 2019) (CHEN *et al.*, 2020)(XU; ZHOU; ZHU, 2018) (YU *et al.*, 2017)(DA COSTA; OLIVEIRA; DE SOUZA, 2021)(WANG *et al.*, 2020) (NIKIFOROVA, 2021) (YASEER; CHEN, 2021) (MANOGARAN *et al.*, 2021) (KORONIOTIS *et al.*, 2020)(METALLIDOU; PSANNIS; EGYPTIADOU, 2020) (KARABEGOVIĆ *et al.*, 2020) (SURESH; UDENDHRAN; BALAMURUGAN, 2020) (ELSISI *et al.*, 2021) (YUAN *et al.*, 2020) (FRANÇA *et al.*, 2021) (QIU *et al.*, 2020) (BACCIU *et al.*, 2017) (YIN; WANG; JHA, 2018)(ALAHI; MUKHOPADHYAY, 2019) (SINGH; SINGH TOMAR, 2019) (HONTI; ABONYI, 2019) (REDDY; MAMATHA; REDDY, 2018) (DJENOURI *et al.*, 2021) (AHMED *et al.*, 2020) (POZA-LUJAN *et al.*, 2020) (JIENAN; XIANGNING; SHUAI, 2021) (LIPPI *et al.*, 2018) (VOICU; PETREUS; ETZ, 2020) (HAMAD *et al.*, 2019) (JACOB *et al.*, 2021) (ALSHAMSI *et al.*, 2017) (XU *et al.*, 2018) (ZHANG *et al.*, 2021) (MAHAKALKAR *et al.*, 2019)(MARKIEWICZ *et al.*, 2019) (GARCIA-MAGARINO; LACUESTA; LLORET, 2017)(GOMES *et al.*, 2019).
Interpretability		(BERTOLI *et al.*, 2021) (MCLAMORE *et al.*, 2019) (PETRARIU; COCA; LAVRIC, 2021) (SHENG *et al.*, 2020) (AHMED *et al.*, 2020)(JUNIOR, 2020) (ASTILL *et al.*, 2020) (SAARIKA; SANDHYA; SUDHA, 2018) (SINGLA; BOSE, 2018) (AKHTER *et al.*, 2019)
Integrity		(KOLAR; BENAVIDEZ; JAMSHIDI, 2020) (AHMED *et al.*, 2021) (TENG *et al.*, 2019) (GADDAM *et al.*, 2020) (MOURTZIS; MILAS; VLACHOU, 2018)
Accuracy		(KOLAR; BENAVIDEZ; JAMSHIDI, 2020) (YAMINI; GANAPATHY, 2021) (CUI, 2020) (VOICU; PETREUS; ETZ, 2020) (ROMAN; ORDIERES-MERE, 2019) (YANG; SHARMA; KUMAR, 2021) (YEH; LIN, 2018) (KURNIABUDI *et al.*, 2018)
Security		(AHMED *et al.*, 2021) (HONTI; ABONYI, 2019) (KHRAIS, 2020) (RAMÍREZ-MORENO *et al.*, 2021a) (OSIFEKO; HANCKE; ABU-MAHFOUZ, 2020) (PUNDIR; SANDHU, 2021)

Sensors Requirements	IoE Category supported	Related Works
Adaptability	Type of Sensors (Who)	(GADDAM *et al.*, 2020) (RUPPERT *et al.*, 2018)(SHIT *et al.*, 2018) (SOLANGI *et al.*, 2018) (GIL *et al.*, 2016) (ROZSA *et al.*, 2016) (STEFANA *et al.*, 2021) (YANG; WEI, 2019) (SONG *et al.*, 2021)(MEERADEVI; MUNDADA; SANJAYKUMAR, 2018) (AKMANDOR; YIN; JHA, 2018)
Usability		(FIROUZI *et al.*, 2018) (GUPTA, 2021) (VISHNU; JINO RAMSON; JEGAN, 2020) (GIL *et al.*, 2016; STEFANA *et al.*, 2021) (ROZSA *et al.*, 2016)
Durability		(MCLAMORE *et al.*, 2019)(PAL *et al.*, 2020)
Mobility	Observation (Where When)	(PETRARIU; COCA; LAVRIC, 2021)
Availability		(JESSE, 2018) (SEHRAWAT; GILL, 2019) (ABRISHAMBAF, 2020) (IQBAL *et al.*, 2018) (SINGA; JADHAV; MATHEW, 2020) (RANA, 2020)
Scalability		(GADDAM *et al.*, 2020) (YAMINI; GANAPATHY, 2021) (PAL *et al.*, 2020) (IQBAL *et al.*, 2018)
Monitorability		(ABDEL-BASSET *et al.*, 2020) (ULLO; SINHA, 2020) (KOCAKULAK; BUTUN, 2017; ULLO; SINHA, 2020) (TAMILSELVI *et al.*, 2020) (RAMAKRISHNA *et al.*, 2019) (PACHAYAPPAN; GANESHKUMAR; SUGUNDAN, 2020) (YAMINI; GANAPATHY, 2021) (GOMBA; NLEYA, 2018) (SOLANGI *et al.*, 2018) (HAMAD *et al.*, 2019) (KAMIENSKI *et al.*, 2018)(SERIKUL; NAKPONG; NAKJUATONG, 2018)
Communication efficiency	Capabilities (How)	(DATTA; SHARMA, 2017) (YU *et al.*, 2017) (FRANÇA *et al.*, 2021)(JACOB *et al.*, 2021)(PURRI *et al.*, 2017)(WU; CHENG; WANG, 2020)(HAMMOUDI; ALIOUAT; HAROUS, 2018)(CABRA *et al.*, 2018) (SILVA *et al.*, 2019) (ABBAS; PRIYA, 2019) (URBINA *et al.*, 2019) (WANG *et al.*, 2019)
Processing efficiency		(CHEN *et al.*, 2020)(YU *et al.*, 2017)(HAMMOUDI; ALIOUAT; HAROUS, 2018)(GRECO; RITROVATO; XHAFA, 2019)(MAITI *et al.*, 2018)(PETRAKIS *et al.*, 2018)(MARKIEWICZ *et al.*, 2019)(KURNIABUDI *et al.*, 2018)(URBINA *et al.*,

Sensors Requirements	**IoE Category supported**	**Related Works**
		2019)(CHAVHAN; KULKARNI; ZILPE, 2021)(CABRA *et al.*, 2018; DIAMANTOULAKIS; KARAGIANNIDIS, 2019)(EICHSTÄDT *et al.*, 2021)
Storage Efficiency		(SHARMA; KAUR; YADAV, 2021)(MOURTZIS; MILAS; VLACHOU, 2018)(HAMMOUDI; ALIOUAT; HAROUS, 2018)(URBINA *et al.*, 2019)(CHAVHAN; KULKARNI; ZILPE, 2021)
Energy efficiency		(SHARMA; KAUR; YADAV, 2021)(OSIFEKO; HANCKE; ABU-MAHFOUZ, 2020)(WU; CHENG; WANG, 2020)(MALDONADO *et al.*, 2018)(DIAMANTOULAKIS; KARAGIANNIDIS, 2019)(KAUR *et al.*, 2017)
Maintainability		(PETRARIU; COCA; LAVRIC, 2021)(SONG *et al.*, 2019)(RUSNACK, 2021)(HALDORAI; RAMU; SURIYA, 2020)(SHARMA; KAUR; YADAV, 2021)(WU; CHENG; WANG, 2020)(CABRA *et al.*, 2018)(URBINA *et al.*, 2019)

3.6 Internet of Everything Database (IoEDB)

IoEDB (https://ioe.cos.ufrj.br/) is an observatory created specifically for cataloging IoE applications and IoE enablers (sensors and actuators). It is a Knowledge Management (KMS) and a tool to conduct distributed and standardized curation of IoE initiatives, expanding the awareness about IoE enabler's interoperability and characteristics.

IoEDB is framed within the theoretical background of the IoE Knowledge-based Taxonomy, proposed in this thesis. It is a serendipitous environment for knowledge creation as it aims to seamlessly provide the foundation from which researchers and developers work together to discover which characteristics of IoE Enablers (knowledge, type, observation, and capabilities) are functional and adequate for specific application design and expected outcomes.

It is a collaborative platform that supports the liveness, evolution, and reusability (KOTIS; VOUROS; SPILIOTOPOULOS, 2020) of the IoE Knowledge-based Taxonomy, preserving it as a suitable live and dynamic artifact considering the IoE pervasive environment.

The main contribution of IoEDB is the curation of IoE enablers (sensors, actuators, information, observation dynamics, and technology resources). Furthermore, the IoEDB project will provide participants to post their knowledge assets and to contribute to the evolution of the taxonomy, creating content related to IoE Initiatives.

As the taxonomy is available online for collaborative improvement, the IoEDB will support its evolution in a top-down evolving process, from the fixed and most general categories (knowledge, type, observation, and capabilities) towards related dimensions and characteristics. From this, it is possible to classify contents, branching, and merging functionalities and features and allow to support multiple streams of work independent of each other. Meanwhile, in the IoEDB platform, users get access to research and practice and smart sensors applications and business cases and connect with peers and users for the purpose of knowledge sharing.

With the growing demand for smart sensors, it is important to address the challenge of creating knowledge sources that provide information about smart sensors and their application in a unified and concise way, regarding distinct domains and possibilities. Besides, IoEDB supports classifying smart sensors related to pre-defined smartness requirements and ranking knowledge of smart sensors related to these requirements presented in Section 3.5. Figure 23 shows the IoEDB homepage.

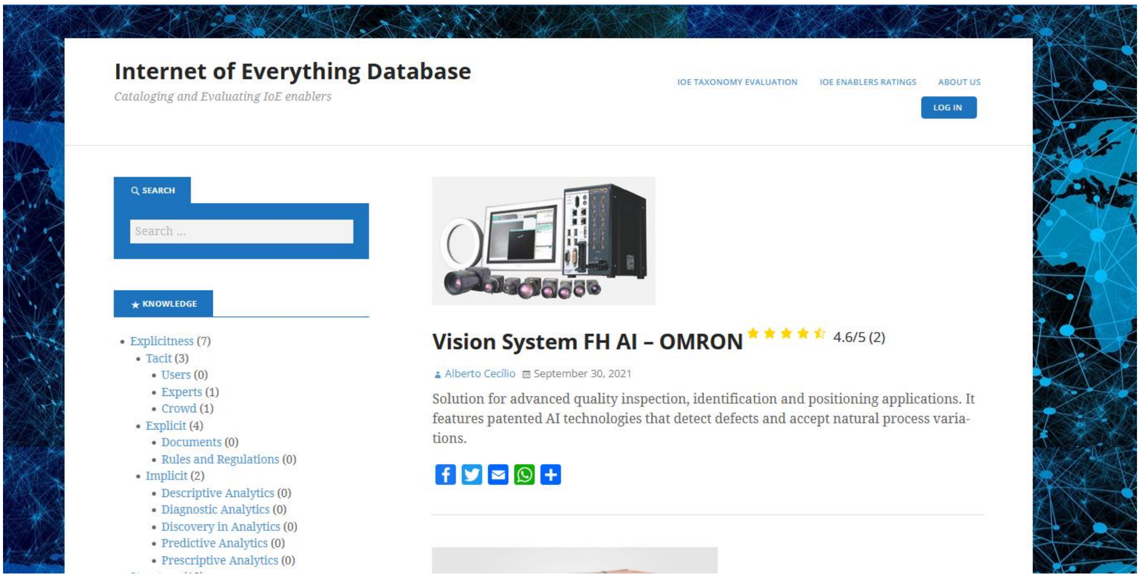


Figure 23. IoEDB Homepage

IoEDB is a web-based application that supports the collaborative design of hierarchical taxonomy structures. Developing a taxonomy usually depends on taxonomy management, and for this, efficient collaboration tools are needed to support the collaborative working task as the taxonomy needs to be maintained frequently by end-users. To support the IoE Knowledge Management strategy, IoEDB is a content management system where content, information, and knowledge resources are appropriately categorized and can be browsed, searched, and accessed according to pre-defined set of categories.

Figure 24 and Figure 26 show an example of IoE Knowledge-based taxonomy (*Explicitness* and *Structure)*, before and after its evolution in IoEDB.

★ KNOWLEDGE

- Explicitness (6)
  - Tacit (2)
  - Explicit (4)
  - Implicit (4)
- Structure (6)
  - Structured (5)
  - Semi-structured (5)
  - Unstructured (2)

Figure 24. Example of Knowledge category, before evolution

★ KNOWLEDGE

- Explicitness (7)
  - Tacit (3)
    - Users (0)
    - Experts (1)
    - Crowd (1)
  - Explicit (4)
    - Documents (0)
    - Rules and Regulations (0)
  - Implicit (2)
    - Descriptive Analytics (0)
    - Diagnostic Analytics (0)
    - Discovery in Analytics (0)
    - Predictive Analytics (0)
    - Prescriptive Analytics (0)
- Structure (18)
  - Structured (15)
    - Relacional Databases (0)
    - Knowledge-Bases (2)
  - Semi-structured (16)
    - Data Sets (15)
      - IoT-Based VPN and Non-VPN (3)
      - Mobile Applications (5)
      - Botnet Attacks (0)
      - Smart Home and Building (1)
      - IoT-Based Smart Farming (1)
      - Healthcare Applications (2)
      - IoT-Based Smart City (1)
  - Unstructured (1)
    - Text files (0)
    - Multimedia content (0)
    - Social media (0)
    - Websites and markup language (0)

Figure 25. Knowledge category - after the evolution

Figure 26 exemplifies the evolution of the explicitness category. In this case, the implicit dimension evolved to address the definition of Siow *et al.* (SIOW; TIROPANIS; HALL, 2018b). This demonstrates that IoEDB integrates research and practice information in a theoretical knowledge base.

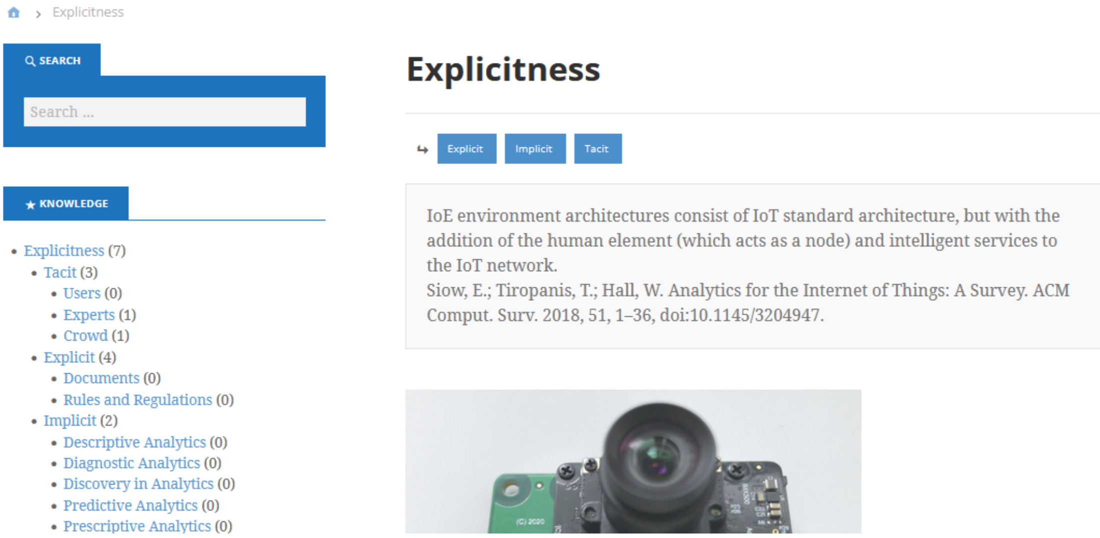


Figure 26. Example of Knowledge category, after evolution

Besides, IoEDB is a prototype for an IoE KM system. Content Management Systems (CMS) are usually mentioned along with KM for the creation and distribution of information. CMS is also about delivering functionalities for supporting knowledge management processes from different perspectives, such as knowledge identification, evaluation, sharing, and so on.

The goal that is targeted in this thesis is to build a user-centered Taxonomy Management System via WordPress to support the curation of IoE enablers and support knowledge sharing between users and experts in the IoE community. For this, WordPress was selected because it is a free and open-source content management system developed in PHP (MySQL or MariaDB database).

To support knowledge management in IoE, the IoEDB has its architecture divided into three layers: presentation, application, and storage layer as shown in Figure 27. The presentation layer is formed by the user interface, where users interact with the system. The application layer is responsible for the management system: access controls, administrative actions, user management, module management, and plugins – these are implemented in a modular way, customizing plugins available on the platform. This modular implementation means that each functionality is isolated in a module, allowing the addition or removal of new functionality when necessary. The IoEDB database layer refers to WordPress standard DBMS, and external data from external data sources or databases.

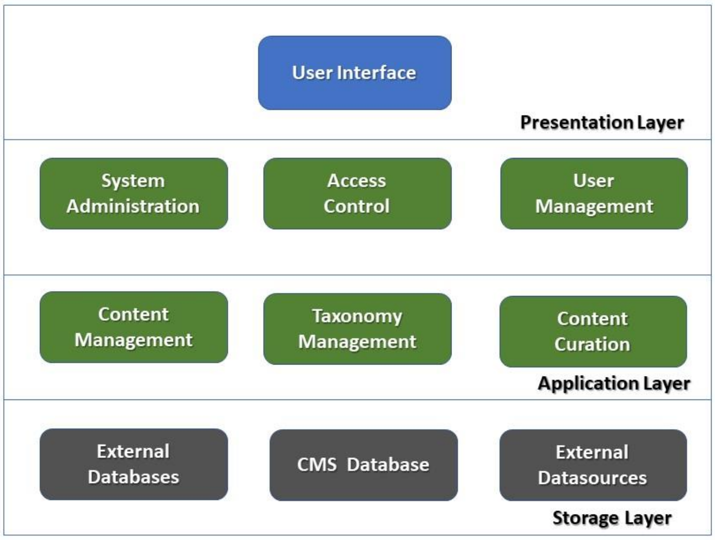


Figure 27. Architecture Layers

IoEDB supports both information that can be automatically collected without user intervention - such as automated search - and information that requires active user contribution - for example, inserting IoE Enablers, uploading a diagram or photo, answering a survey, tagging a project or application.

According to BOOCH *et al.* (1999), use case diagrams are essential to model the behavior of a system, and important for visualizing, specifying, and documenting the behavior of an element. The diagram in Figure 28 presents a set of use cases, along with their actors and relationships. A use case involves modeling the context of a system. The list of IoEDB Use Cases – and their respective descriptions – are presented in Table 9.

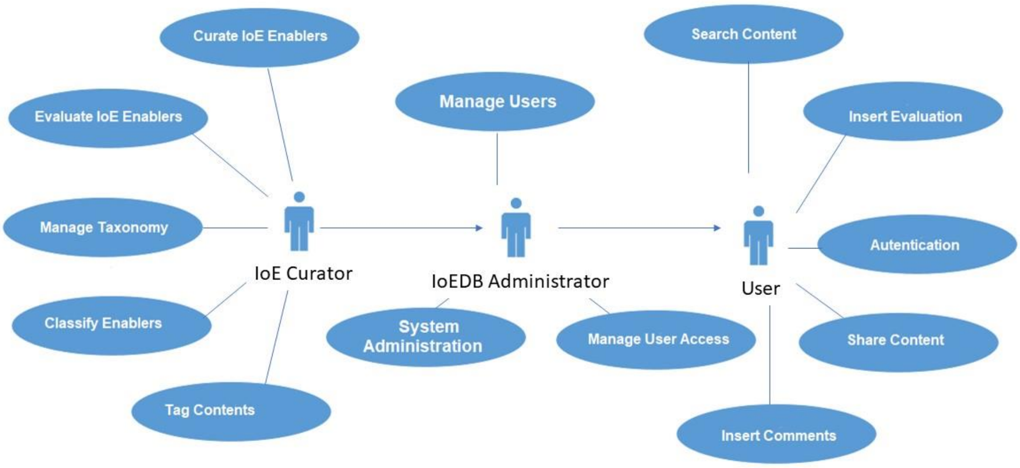


Figure 28. IoEDB use cases

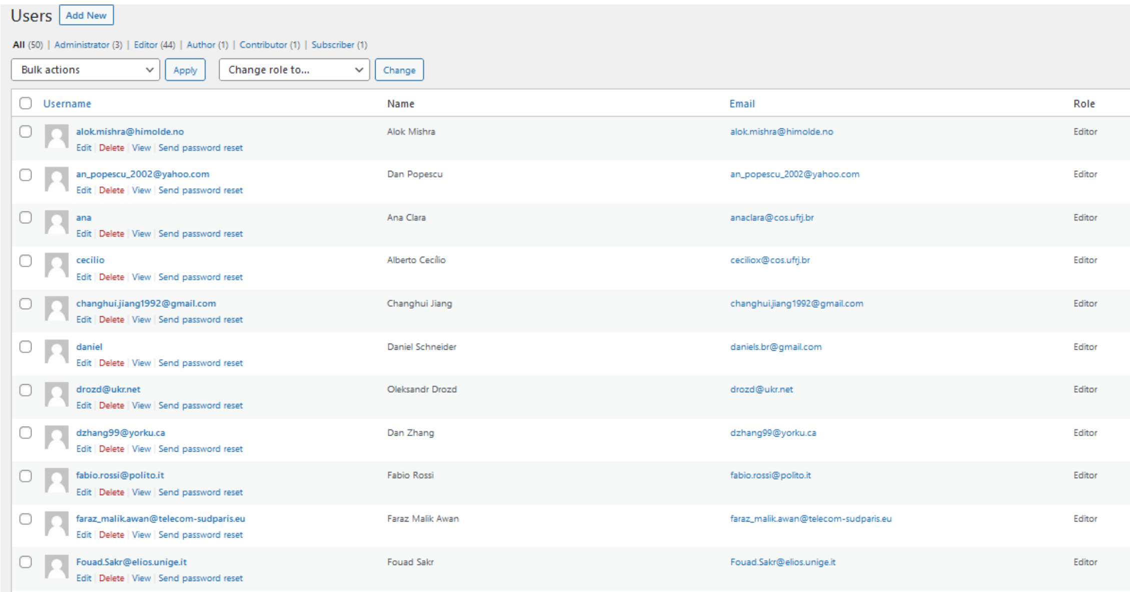
Table 9. IoEDB Use cases description

Entity	Use Cases	Description
Administrator	Manage user access	Register users in the System
	System Administration	Support CMS administrator
	Manage users	Manage users roles
User	Search Content	Search IoE Enablers and applications
	Insert Evaluation	Evaluate available IoE Enablers
	Authentication	User authentication
	Insert Comments	Comment contents
	Share Content	Share IoE contents
Enabler Curator	Curate IoE Enablers	Manage registration information of IoE Enablers
	Manage IoE Enablers	Insert IoE Enabler information
	Manage Taxonomy	Manage the Taxonomy categories and dimensions
	Tag Contents	Insert related tags
	Evaluate IoE Enablers	Classify IoE enabler in categories and dimension

I. User roles

Default CMS user roles were associated with each role in IoEDB: Administrator, Editor (as IoE Curator), and User (as a subscriber). WordPress default user's roles are used to grant permissions to enable or deny access to insert enablers, posts, categories, tags, and insert content in the system.

IoEDB Administrator manage users and the CMS System. The user’s role are allowed to search for specific information in IoEDB, evaluate smart sensors (optionally), share content (optionally), and comment on posts



Users Add New

All (50) | Administrator (3) | Editor (44) | Author (1) | Contributor (1) | Subscriber (1)

Bulk actions Apply Change role to... Change

Username	Name	Email	Role
alok.mishra@himolde.no Edit | Delete | View | Send password reset	Alok Mishra	alok.mishra@himolde.no	Editor
an_popescu_2002@yahoo.com Edit | Delete | View | Send password reset	Dan Popescu	an_popescu_2002@yahoo.com	Editor
ana Edit | Delete | View | Send password reset	Ana Clara	anaclara@cos.ufrj.br	Editor
cecilio Edit | Delete | View | Send password reset	Alberto Cecílio	ceciliox@cos.ufrj.br	Editor
changhui.jiang1992@gmail.com Edit | Delete | View | Send password reset	Changhui Jiang	changhui.jiang1992@gmail.com	Editor
daniel Edit | Delete | View | Send password reset	Daniel Schneider	daniels.br@gmail.com	Editor
drozd@ukr.net Edit | Delete | View | Send password reset	Oleksandr Drozd	drozd@ukr.net	Editor
dzhang99@yorku.ca Edit | Delete | View | Send password reset	Dan Zhang	dzhang99@yorku.ca	Editor
fabio.rossi@polito.it Edit | Delete | View | Send password reset	Fabio Rossi	fabio.rossi@polito.it	Editor
faraz_malik.awan@telecom-sudparis.eu Edit | Delete | View | Send password reset	Faraz Malik Awan	faraz_malik.awan@telecom-sudparis.eu	Editor
Fouad.Sakr@elios.unige.it Edit | Delete | View | Send password reset	Fouad Sakr	Fouad.Sakr@elios.unige.it	Editor

Figure 29. User management screen

II. Comments

The functionality of "*Post Comments*" provides an opportunity for knowledge sharing. The users' comments are automatically posted in specific debate spaces (posts or pages). The comments are moderated by the system administrator. Furthermore, by selecting a comment, several buttons are made available to the user, allowing anyone to participate in the debate by posting messages, replying to previous ones, up or down to view others' commentaries.

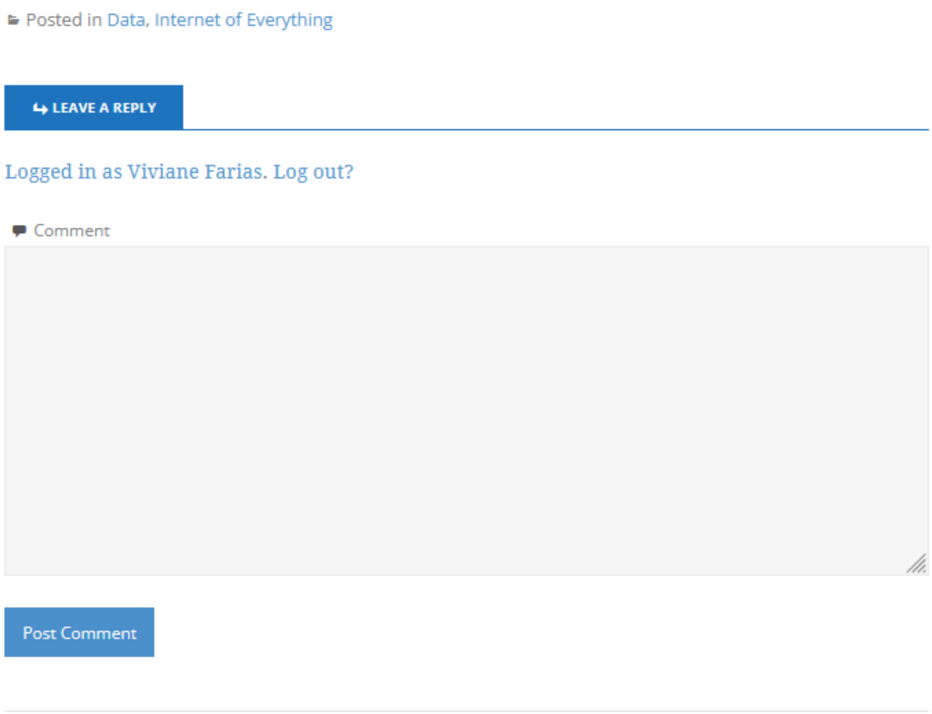


Figure 30. Post comment screen

III. Taxonomy Management

Besides the CMS administrator, there are 2 distinct user roles defined for IoEDB: the IoE Curator and the User.

To insert new IoE enablers or dimensions in IoE taxonomy, the user must be registered in the system as a Curator (editor).

Regular users are allowed to search for specific information in IoEDB or evaluate smart sensors regarding smartness requirements.

As it can be seen in Figure 31, IoEDB provides its users with some information about IoE Enablers. To insert a new IoE Enabler, the curator must provide its name, description, proposition paper and classify it regarding IoE category and dimension and

Besides providing basic information about the IoE Enabler, such as title and description, the Curator may also upload several different knowledge resources such as images, videos, documents (e.g., news, white papers), and links to other resources on the Internet (e.g., official website). The user can also inform the research paper published and information related to the URL.

Figure 32, Figure 33, Figure 34, Figure 35 exemplifies IoE enabler classification related to the IoE taxonomies dimensions.

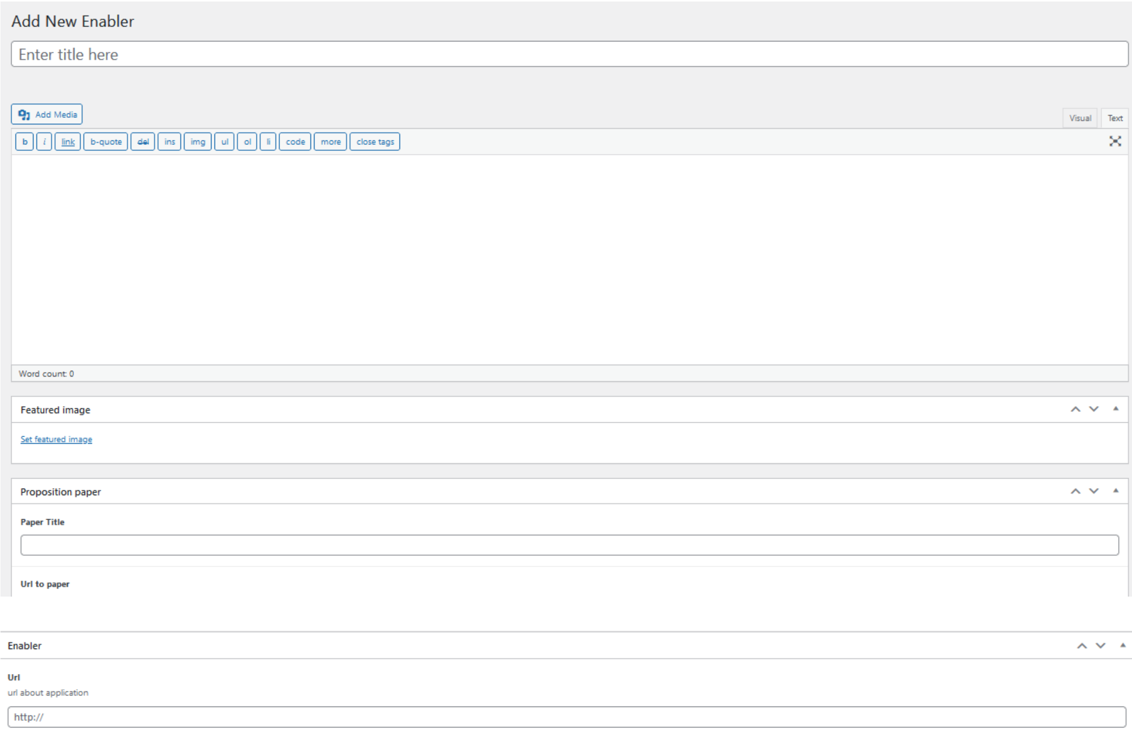


Figure 31. Add New Enabler screen

IV. Using the Taxonomy

The user can select one of the dimensions and related characteristics or use the *+Add New* link beside each category to insert a new dimension for the related category, evolving the taxonomy. It is also possible to search the most used dimensions in which previous users classified other IoE Enablers.

It is important to remark that if a given user inserts a new dimension, the new one must be inserted considering the hierarchy of dimensions in the same category.

During the cataloging process, it is possible to realize the most used categories, contributing to achieving greater convergence of the selected dimensions or to provide innovative categories for newly observed IoE enablers characteristics.

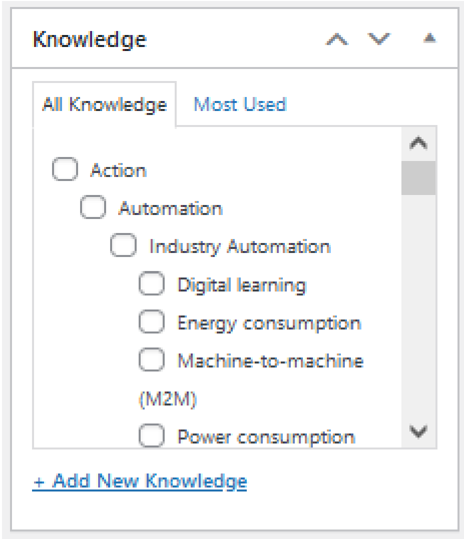


Figure 32. Knowledge Category and dimensions

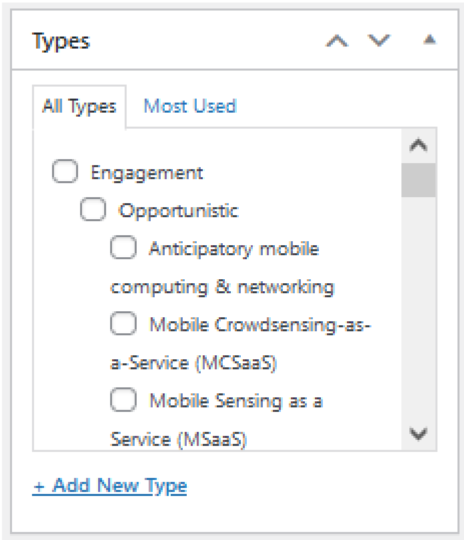


Figure 33. Type Category and dimension

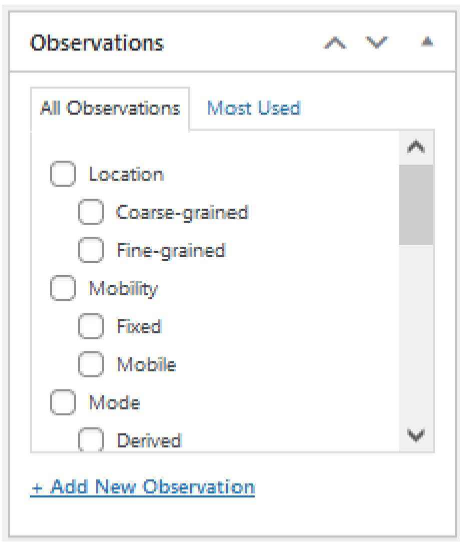


Figure 34. Observation Category and dimension

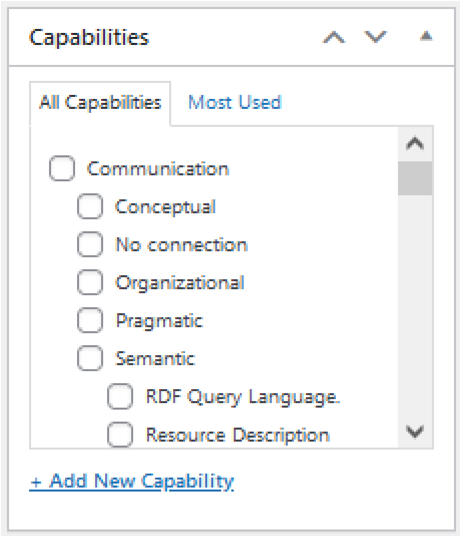


Figure 35. Capabilities category and dimensions

V. Tagging IoE Content

The curator is allowed to tag the content or associate the enabler to specific tags in the system.

Figure 36. Tag Cloud

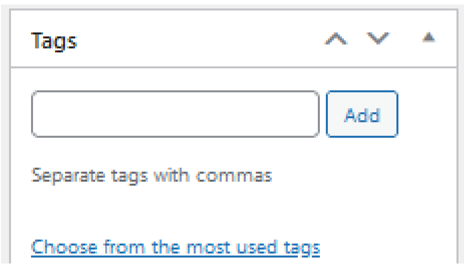


Figure 37. Insert tag screen

It is important to remark that if a dimension is too different from those available in the system, the user will be asked to justify his opinion in a brief description. Leaving a reference or theoretical foundation about the new dimension is also recommended for users to support a body of knowledge about the IoE Taxonomy.

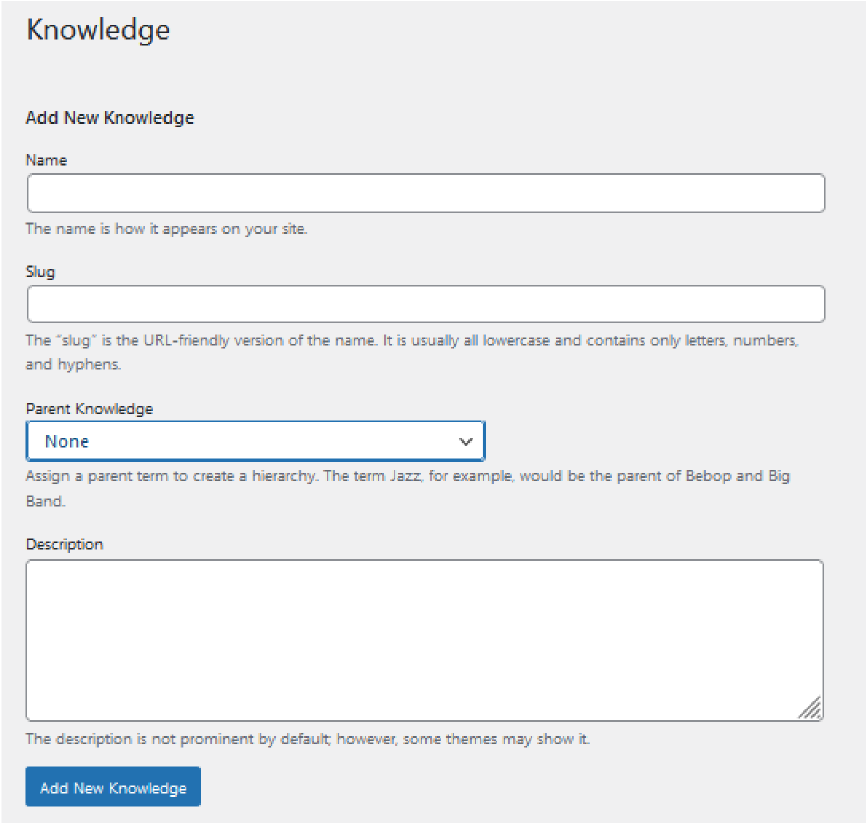


Figure 38. IoE DB insert new dimension screen

VI. Post and Forum

Post and related forums are another functionality that is a platform for knowledge externalization and knowledge sharing about IoE related content. Curators can create posts and moderate its forums to support sharing of information about IoE Enablers. The results of the moderated comments may create a serendipitous "debate" available both for users, experts, and the IoE community of interest. This space provides an opportunity for knowledge creation.

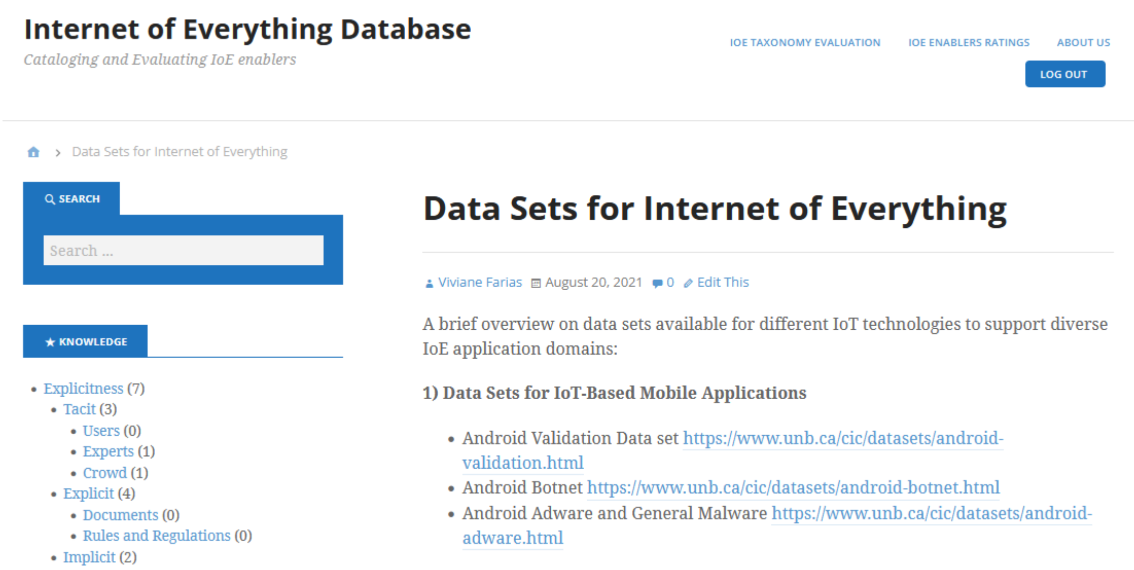


Figure 39. Post screen

VII. Taxonomy evolution screen

For each dimension, the user can choose one or more items (characteristics) already available in the list of options or easily include a new dimension on the same screen where the application is cataloged. For example, Figure 40 shows the insert dimension screen on the IoEDB system.

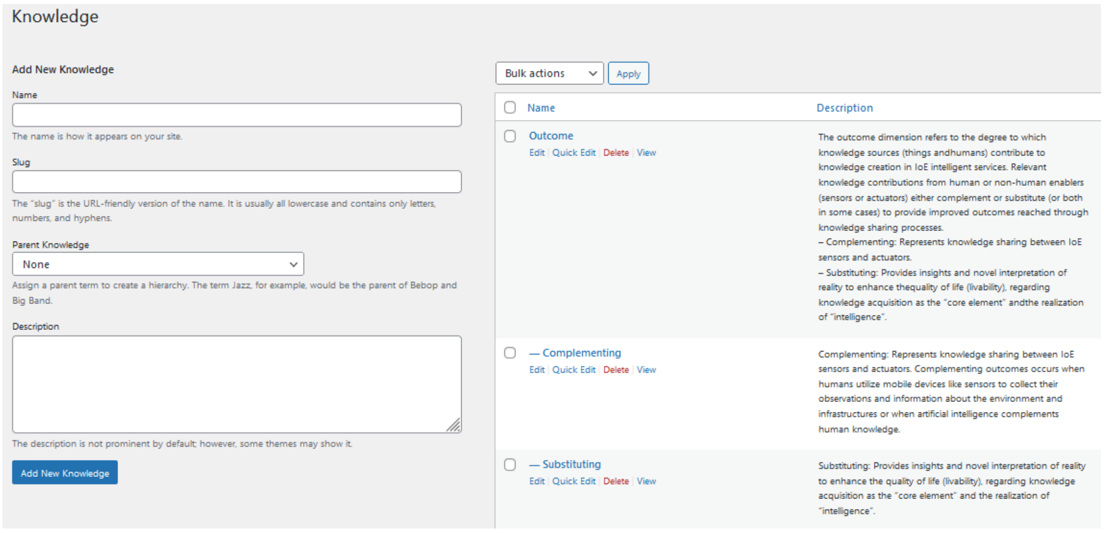


Figure 40. Insert new taxonomy dimension

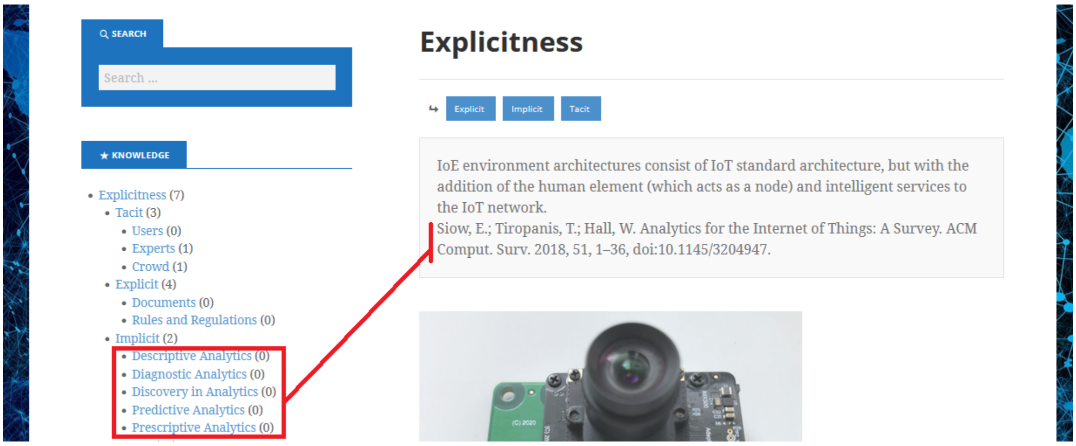


Figure 41. IoEDB body of knowledge example

VIII. IoE Enabler Evaluation

The application architecture allows the researcher to create IoE hierarchical classifications related to the IoE entity (the application). In this way, it is possible to associate the application with one or more IoE categories.

From the IoE knowledge-based taxonomy dimensions, starting with the most general categories (knowledge, type, observation, and capabilities), the user selects dimensions and characteristics previously derived from a theoretical foundation, revealing the resulting IoE enablers composition for a given IoE application.

The IoEDB platform shows IoE Enabler information and evaluation according to smartness requirements Figure 42.

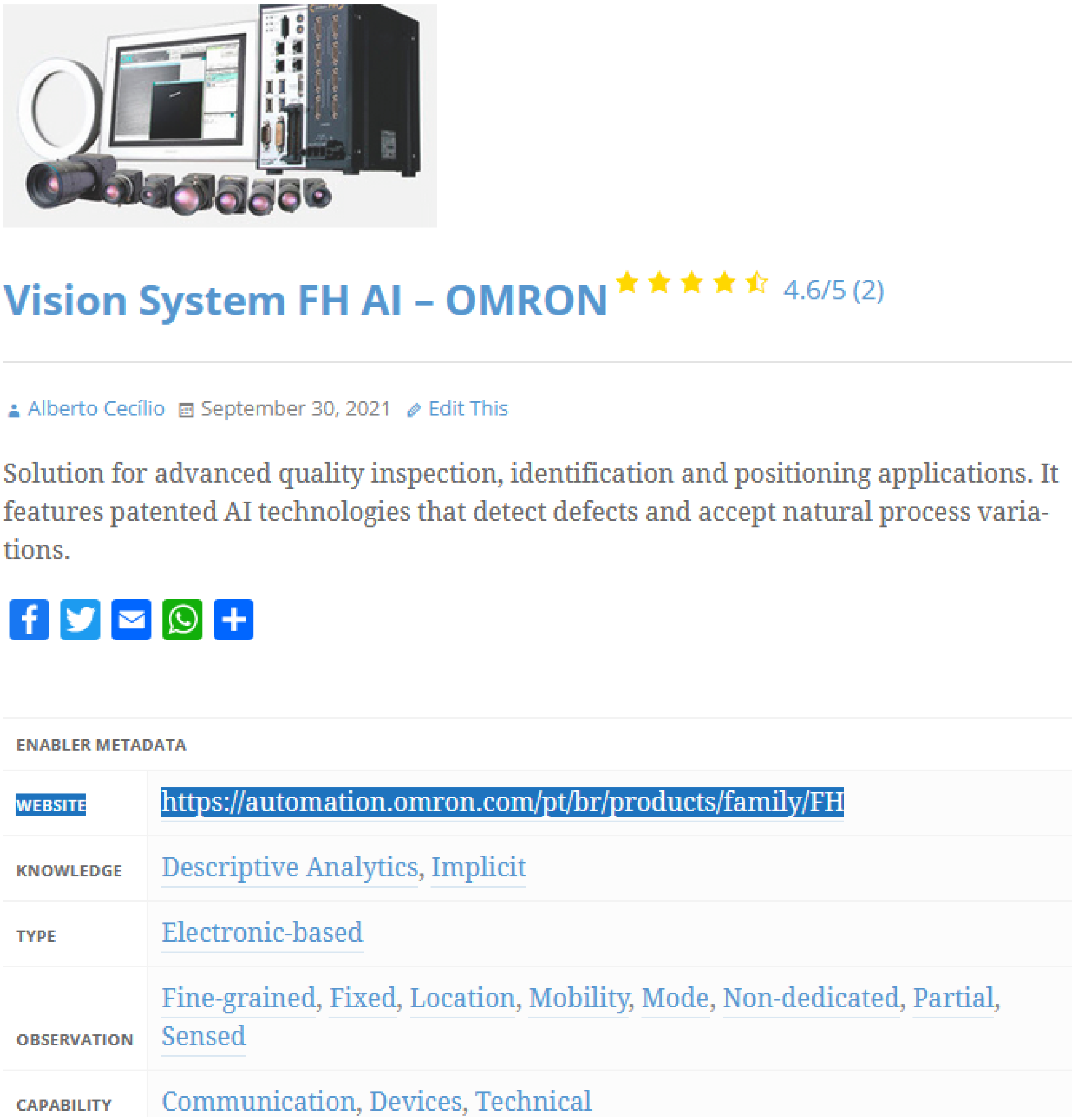


Figure 42. IoE Enabler screen

IoE Curator can evaluate IoE Enablers regarding requirements presented in Section 3.5. The score is calculated using a Rating Algorithm (Average or Bayesian Average).

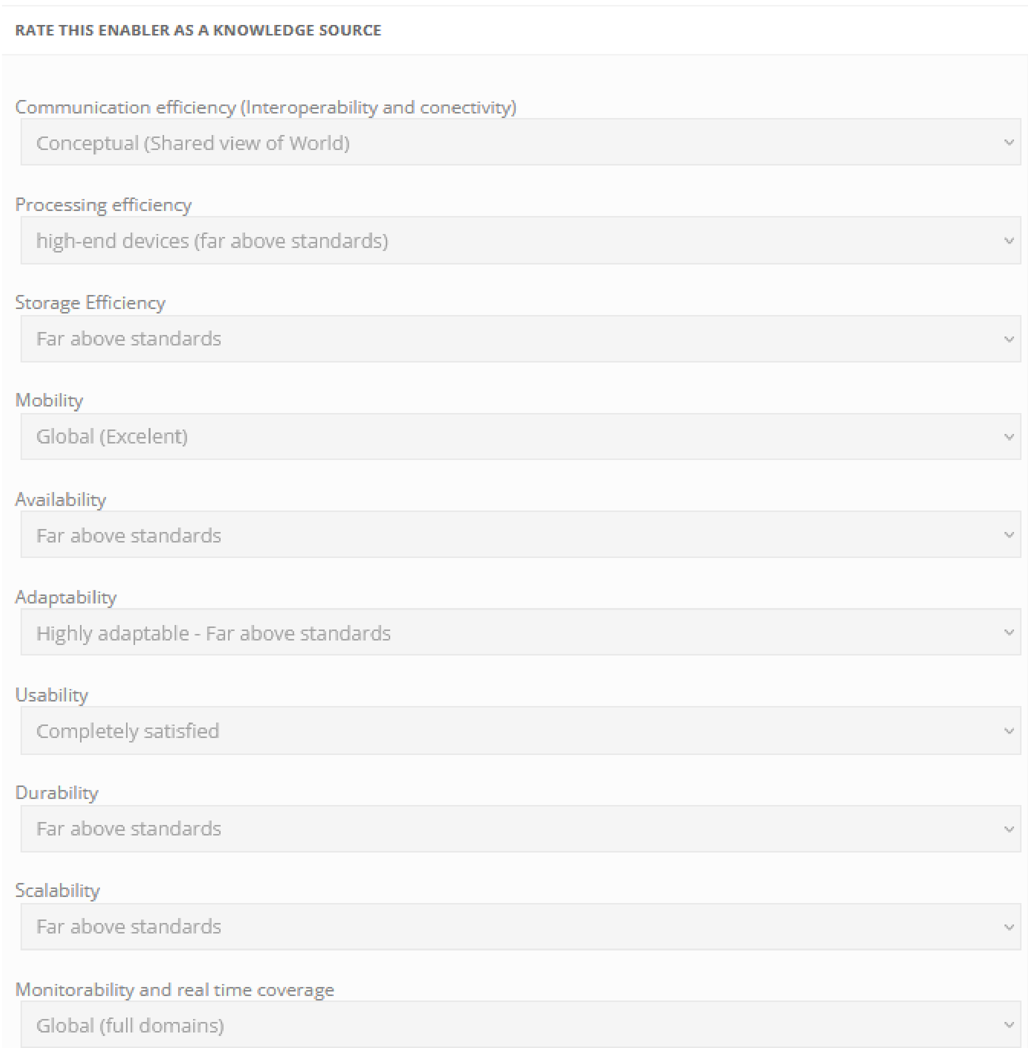


Figure 43. Ranking IoE Enabler

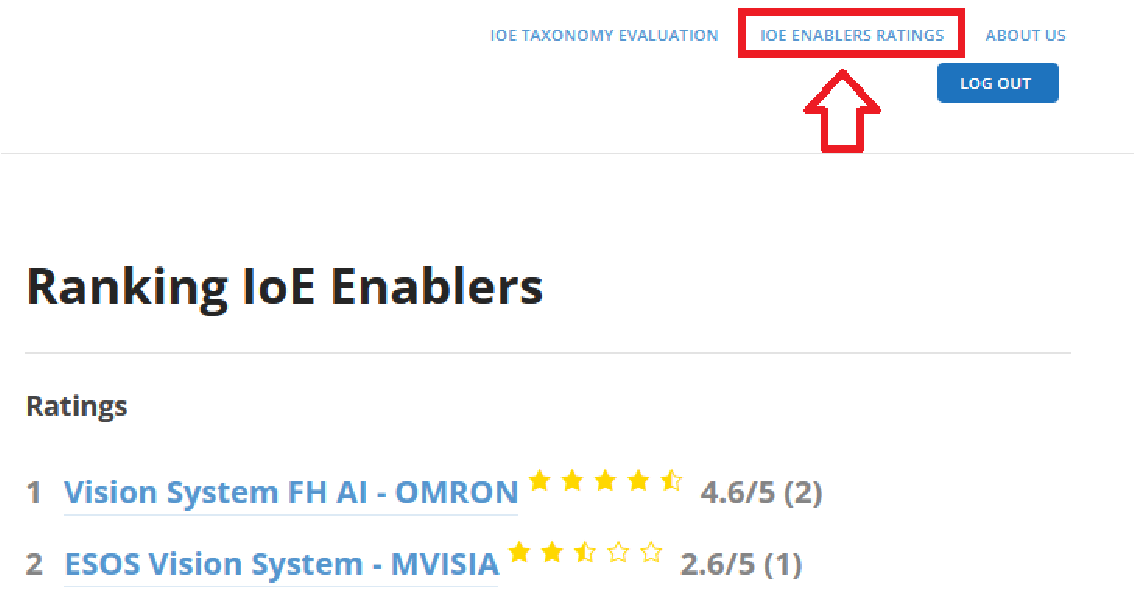


Figure 44. IoE Enabler ranking

4 Evaluation Phase

This Chapter evaluates the proposed artifacts. In Section 4.1 e 4.2, the IoE Knowledge-based Taxonomy is used to support identifying and ranking knowledge in IoE applications and smart sensors. Next, an approach for Quality of Service is presented to validate Smartness requirements proposed in Section 3.5 and demonstrates IoEDB functionalities for ranking knowledge in Smart Sensors. Finally, a fictitious case study with an IoE system in the military domain demonstrates the application of the IoE Integrated Knowledge Management Model to conduct a KM strategy.

Evaluation of design artefacts provides feedback for further development and (if done correctly) assures the rigor and high academic standards and research quality (VENABLE; PRIES-HEJE; BASKERVILLE, 2016). In DSR methodology, researchers must rigorously demonstrate the utility, quality, and efficacy of the design artefact using well-executed evaluation methods. However, on March 2020, the COVID-19 global pandemic had an unexpected and profound impact on our daily lives and so in this thesis research activities, especially in this final phase of Evaluation. The original observational study planned to evaluate the IoE IKM Model considering 3 case studies: in academia, industry, and military domains. Due to restrictions, the pandemic changed the evaluation to fictitious case study instead, presented in Section 4.3. And for evaluation of sensors smartness, the impact was mitigated by considering the evaluation of knowledge in crowdsourcing applications (Section 4.1) and ranking industry IoE sensors smartness (Section 4.2).

4.1 Ranking Knowledge in IoE Applications

The IoE Integrated Knowledge Management Model, in its Second Quadrant: (Establishment (E) and Evaluation), defines that towards service evolution in IoE, sensors and actuators attributes (which contributes to knowledge creation) should be qualitatively evaluated by a composition of characteristics in IoE applications. For this evaluation, selected categories (knowledge, type, observation, and capability) from the IoE knowledge-based taxonomy (FARIAS DA COSTA; OLIVEIRA; DE SOUZA, 2021), support the qualitative analysis as follows: (a) knowledge sources regarding the kind of knowledge provided, (b) the type of sensors and actuators, (c) the observation within ever-changing contexts and (d) the technological capabilities of sensors.

In this sense, specific elements, adapted from (GUTWIN; GREENBERG, 2004) were used to answer basic "who, what, where, when, and how" questions related to awareness of sensors and actuators in IoE context, as presented in Table 10.

Table 10. Categories and Elements of awareness applied to IoE domain

Elements of workspace awareness			***IoE Taxonomy***
Category	***Element***	***Specific questions***	***Categories***
What	Action Intention Artifact	What are sensors doing? What are they willing to do? What kind of knowledge do they provide?	Knowledge
Who	Presence Identity Authorship	Who are the IoE enablers? Who is doing what? Who is the knowledge source?	Type of sensors
Where When	Location Gaze	Where are IoE enablers? When are they observing?	Observation
How	View Reach	How much can they see? How far they can reach?	Capabilities

The proposal depicted in Figure 45, presents four categories: knowledge, type of sensors, observation and capability, and detailed knowledge category in its dimensions (explicitness, outcome, action, trust, and structure (FARIAS DA COSTA; OLIVEIRA; DE SOUZA, 2021). These dimensions are described below:

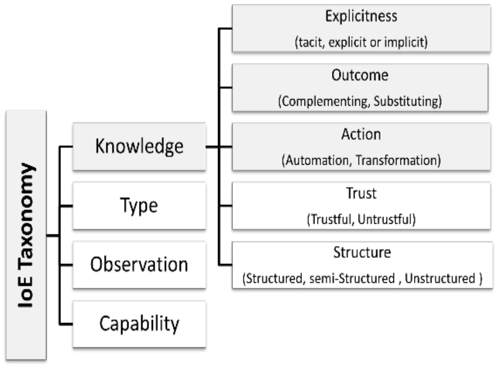


Figure 45. IoE Taxonomy: Knowledge Category

To evaluate the IoE Knowledge-based taxonomy's practical applicability and its benefits in evaluating knowledge in IoE applications to support the research goal of "*leveraging awareness of the knowledge hierarchy, considering knowledge interaction and transformations of IoE enablers*". The categories from (FARIAS DA COSTA; OLIVEIRA; DE SOUZA, 2021) and elements of awareness (GUTWIN; GREENBERG, 2004) were considered and applied to the IoE domain, as presented in Table 10.

For this, this work evaluated knowledge sources and characteristics of 40 applications observed by (MELO *et al.*, 2017) in a Crowd Application Database (http://cadb.demoro.net).

Participatory sensing enables ordinary citizens to share data (from personal experiences or the environment in which they find themselves). However, to understand the transformative potential of collaboration between people and things in IoE applications (M2H, M2M, H2H), there is a research gap, regarding insights into the characteristics of knowledge creation, actions, and transformations provided using IoE applications and the value created from people and things in this context.

According to (MELO *et al.*, 2017), there is a need to create mechanisms to ensure users the purpose of the use of their data or inform users that their data is being collected, to generate a sense of trust.

Explicitness dimensions were chosen from the knowledge category of the IoE taxonomy proposed in (FARIAS DA COSTA; OLIVEIRA; DE SOUZA, 2021) because understanding and managing knowledge in IoE enablers are surely to be a key challenge in IoE applications systems. The selected sub-dimensions of the knowledge category (explicitness, outcome, and action) have specific attributes, which are the values that the sub-dimensions may take, as presented in Table 11.

The selected questions are: "*what kind of knowledge is provided by knowledge enablers*", to evaluate knowledge in terms of its "*explicitness*" to what degree of tacit, explicit, and implicit knowledge is used in IoE application. *Action* dimension supported the evaluation of value created in IoE applications, provided in automation of processes and transformation of life in a disruptive environment. And the intention of knowledge sources as collaborators (complements) or knowledge providers (substitutes) was evaluated in terms of *Outcomes* provided.

The attributes are listed in Table 11, for the degree to which each characteristic contributes to the knowledge sub-dimension (explicitness, outcome, and action). To support qualitative evaluation, attributes levels were defined: 3 (high), 2 (moderate), or 1 (low) and 0 (zero) for not applicable attributes.

Table 11. Qualitative attribute levels

Characteristic	***Attribute***
Tacit	3. **high**: participatory sensing and expert human knowledge 2. **moderate**: crowdsourcing or thing-human collaboration 1. l**ow**: opportunistic sensing
Explicit	3. **high**: expert and critical knowledge explicit in data sources 2. **moderate**: support of explicit knowledge in data sources 1. **low**: eventual use of explicit knowledge on demand
Implicit	3. **high**: discovery and predictive analytics, to predict future outcomes or prescriptive analytics to provide the best course of action and foresight on time 2. **moderate**: diagnostic analytics to find out the root cause and explanations for the sensor data 1. **low**: descriptive analytics when data are decoded, interpreted in context,
Complement	3. **high**: provide foresight on time considering uncertainty 2. **moderate**: provide insights about what happened and context awareness 1. **low** give hindsight and information for decision-support

Characteristic	*Attribute*
Substitute	3. **high**: provide critical knowledge that leads to the best course of action to act on foresight promptly 2. **moderate**: provide knowledge using data to detect something novel to support decision making 1. **low** hindsight on what and why things have happened
Automation	3. **high**: automated without human intervention. 2. **moderate** automated with little human intervention. 1. **low**: physical components act as a connection bridge to network cyber-physical things.
Transformation	3. **high**: create pervasive and global cyber-physical systems (CPS) ubiquitous cyber-physical world 2. **moderate** use of artificial intelligence, machine learning to support actions and services 1. **low** data-intensive applications and services

From the 40 applications analyzed from (MELO *et al.*, 2017), a range of 11 top knowledge-intensive applications were selected: Noisetube (MAISONNEUVE *et al.*, 2009), CenceMe (MILUZZO *et al.*, 2008), MicroBlog (GAONKAR *et al.*, 2008), Ubifit Garden (CONSOLVO *et al.*, 2008), GarbageWatch (ESTRIN *et al.*, 2010), Galaxy Zoo (MASTERS *et al.*, 2011), eBird (WIGGINS, 2011), SenSay (SIEWIOREK *et al.*, 2003), Jog Falls (NACHMAN *et al.*, 2010), MobAsthma (KANJO *et al.*, 2009) e Transafe (HAMILTON *et al.*, 2011). This evaluation was presented in CSCWD 2021 Conference.

- Noisetube (MAISONNEUVE *et al.*, 2009) is a people-centric data collection application. The main fact is that people play an important role in perceiving what they consider annoying noise.
- In Micro-Blog (GAONKAR *et al.*, 2008), the transformation is provided by “the collaborative inputs from phones” that “may enable a high-resolution view of the world”. It is a people-centric application that uses sensors of participatory/sensory inputs from local surroundings.

Micro-Blog can be a deployable tool for sharing, browsing, and querying global information.

- In CenceMe (MILUZZO *et al.*, 2008), it is important to note the “different degrees of a user’s sensing presence”. It exploits off-the-shelf sensor-enabled mobile phones to automatically infer people’s sensing presence. It is a device-centric application with sensing and classification algorithms.
- In Ubifit Garden (CONSOLVO *et al.*, 2008), the activity inference (data) and the mobile display (thing) “encourage physical activity” for people in on-body sensing, activity inference.
- In Garbage Watch (ESTRIN *et al.*, 2010), people are actuating in “capturing relevant information to improve the recycling program”. These systems can be leveraged by individuals and communities to address a range of civic concerns, from safety and sustainability to personal and public health.
- In Galaxy Zoo (MASTERS *et al.*, 2011), the knowledge sharing between astronomers and users' activities is the value created by the application, optimizing the classification of shapes in contrast to a completely automated approach and classifications.
- For eBird (WIGGINS, 2011), knowledge sharing with a global community of educators leads to a better understanding of bird distribution. eBird is an online checklist program that enables reports and access to information about birds, promoting improved scientific outcomes.
- SenSay (SIEWIOREK *et al.*, 2003) provides communication between people and the application (things). The application makes suggestions to users so that they can make better decisions about their lives. It combines sensory data, user information, and history information to create a context-aware phone.
- Jog Falls (NACHMAN *et al.*, 2010) connects expert users (nutritionists) with their patients. The application works closely with physicians. The

main goal of the system is to empower patients to manage their lifestyles.

- In MobAsthma (KANJO *et al.*, 2009), the patients' locations are made available (by things) to allergists and asthma specialists (people) to investigate the personal relationships between asthma attacks and exposure to air pollution (data).

- Transfer (HAMILTON *et al.*, 2011) captures and analyses public perceptions of safety to deliver `crowdsourced' collective intelligence about places.

These applications are intrinsically composed of knowledge-intensive tasks for the expected purpose and value creation. The transformations or automation provided by these applications consists of conversions of tacit-explicit-implicit knowledge when people, things, and data are connected in the IoE environment to provide relevant services and collective intelligence.

Application characteristics were analyzed, evaluated the degree of tacit, explicit, and implicit knowledge, and identified the requirements for value created by the IoE applications about its expected outcomes and actions supported by intelligence in the IoE network. This analysis will support future IoE application requirements. While many of these applications provide useful features, this work has demonstrated that there are still gaps in fully addressing ranking knowledge in IoE applications. Considering the IoE knowledge-based taxonomy categories (explicitness, outcome, and action), this conceptual analysis facilitates the visual comparison of how knowledge contributes to the value creation of the applications surveyed, as illustrated in Figure 46, Figure 47, and Figure 48.

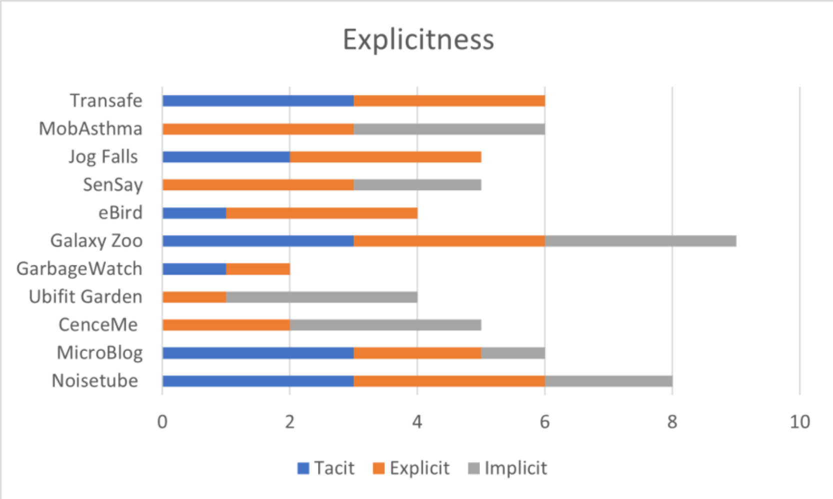


Figure 46. Explicitness evaluation

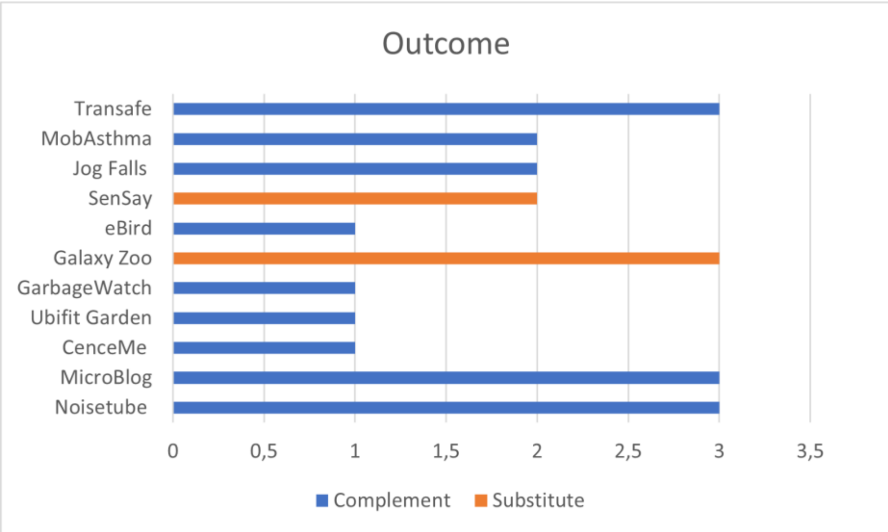


Figure 47. Outcome

As presented in Figure 48, in Galaxy Zoo, the knowledge sharing between astronomers (experts) and users' activities (wisdom of the crowd) and implicit knowledge in artificial intelligence and systems of its domains reflects in the value created by the Galaxy Zoo application, representing the highest rank of knowledge between the applications considered in this study.

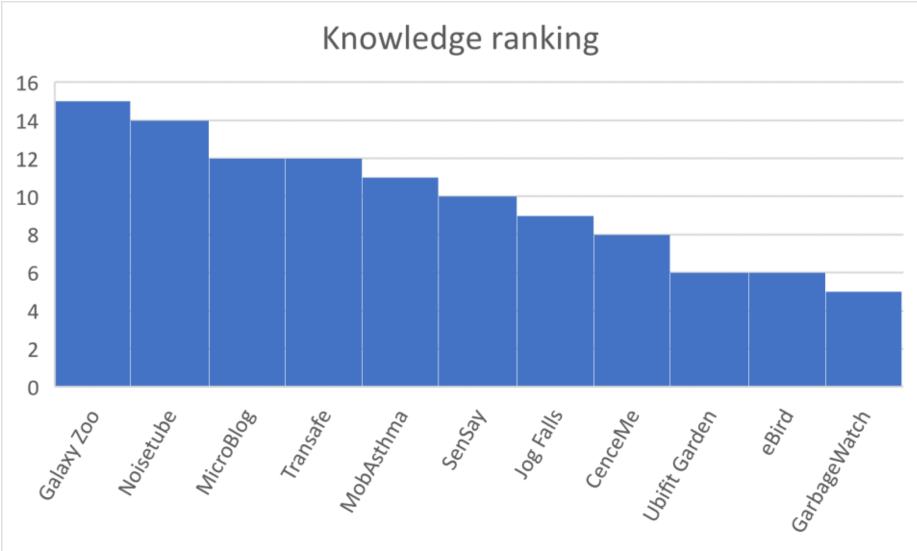


Figure 48. Knowledge ranking in IoE applications

4.2 Ranking knowledge of Smart Sensors in Industrial Internet of Things

The IoE Integrated Knowledge Management Model, in its Second Quadrant: (Establishment (E) and Evaluation), defines that, to support intelligent services in the IoE context, sensors and actuators attributes should be qualitatively evaluated by a composition of characteristics that contributes to knowledge creation.

The following evaluation is limited to electronic sensors and actuators used in Industry 4.0. Considering the definitions of smart sensors discussed in Section 2.2, characteristics were selected to characterize an intelligent sensor or actuator. The IoE Taxonomy dimensions were selected from Knowledge, Type, and Capability categories, and, from them, seven characteristics were also chosen according to their semantic value for intelligence classification of smart sensors.

Figure 49 presents IoE Knowledge-based taxonomy and the selected dimensions are represented in yellow.

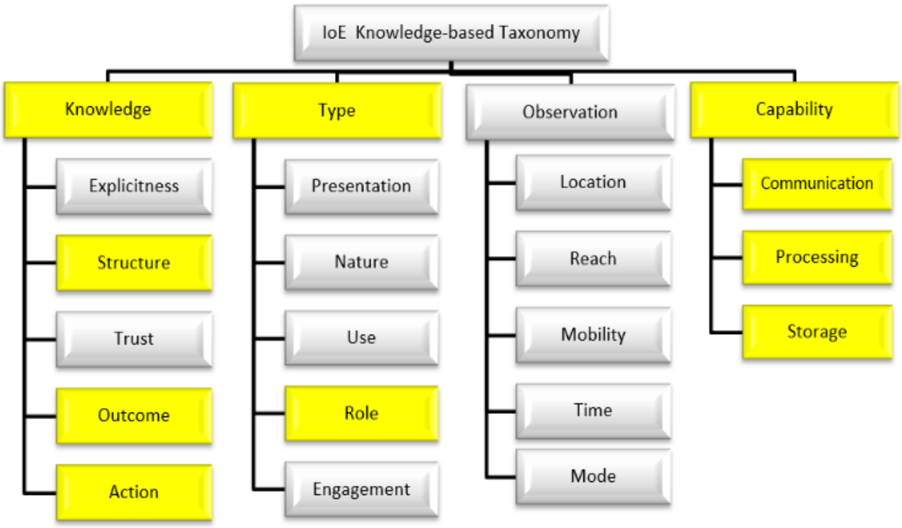


Figure 49. Selected dimensions (in yellow)

Regarding Knowledge category:

• Outcome: Refers to what extent smart sensors contribute to value creation and IoE intelligent services. Smart sensors contribute to knowledge creation (in collaboration processes) or may represent the main knowledge sources of the smart environment, substituting all others.

• Action: Refers to knowledge in action. Smart sensors may support the automation of processes or may be a main driver of the IoE transformation experience.

• Structure: Refer to raw data, and data transformations supported by smart sensors. Sensor data may be unstructured, semi-structured, or structured.

Regarding Type category

• Role: Refers to smart sensors task as sensors or actuators, perform sensing and/or actuating functions and according to defined rules under various scenarios.

Regarding Capability category

• Communication: Refers to sensors' ability to communicate and change local information. It varies from device to device, device to server, or server to server.

• Processing: Refers to sensor's ability to process data locally or in the cloud/fog or edge infrastructure.

• Storage: Refers to the storage capacity of sensors at cluster-level, network-level, or device-level.

The evaluation will apply metrics to evaluate smart sensors. It is assumed that when a feature adds little relevance to the smart status, it receives a score of 1, when the contribution is median, it receives a 2 score, and when it is relevant and contributes to overall smartness it receives a 3 score. The scores and classifications are presented in Table 12. The scores and definition are empiric values just to demonstrate the IoE knowledge-based taxonomy applicability and future research will address formal evaluation methods.

Table 12. Score values

IoE knowledge-based Taxonomy		**Score**		
		1	**2**	**3**
Knowledge	Outcome	Complement	Substitute	Both
	Action	Automation	-	Transformation
	Structure	Unstructured	Semi-structured	Structured
Type	Role	Sensor	Actuator	Both
Capability	Communication	Device to device	Device to server	Server to server
	Processing	Local	Fog	Cloud
	Storage	Device-level	Network-level	Cluster -level

The maximum intelligence score that a sensor may reach is 21 points, given that it will receive 3 points for having at the highest level (related to 7 taxonomy dimensions). Similarly, the minimum score will be 7 points for having only the minimum requirements (1 point for each dimension). From this score range (7 to 21 points), the intelligence level was divided into three levels: low intelligence (low), medium intelligence (medium), and high intelligence (high). The metrics and intelligence levels are shown in Figure 50.

Final Score	**Levels**	
Minimum 7 pts.	Low	Equal or higher than 7 and less or equal than 11
	Medium	Equal or higher than 11 and less or equal than 16
Maximum 21 pts.	High	Higher than 16

Figure 50. Smartness scores and intelligent levels

To exemplify the qualitative approach to evaluate the degree of intelligence in smart sensors, sensors from different categories were selected, with distinct characteristics and application domains: image sensors, temperature sensors, proximity sensors, speed sensors, and sound sensors.

1. Image Sensors: Image sensors convert electrical signals triggered by light into optical form to display or store the images electronically. Examples are digital cameras, night vision cameras, radar, sonar, thermal imaging, biometrics (SEHRAWAT; GILL, 2019).

Table 13. Case Study with Image Sensors

Relevant IoE dimensions and characteristics *		Smart Sensor		
		FH Series Vision System OMRON Industrial	SENS Vision Sensor with CVU Processing Unit	IMX500 Intelligent Vision Sensor
Knowledge	Outcome	Both	Complement	Complement
	Action	Transformation	Automation	Automation
	Structure	Structured	Structured	Structured
Type	Role	Both	Sensor	Sensor
Capability	Communication	Server to server	Device to server	Device to device
	Processing	Local	Edge	Edge
	Storage	Device-level	Device-level	Device-level
Final Score		**19 (high)**	**12 (Medium)**	**11 (Low)**

* Dimensions selected from IoE Knowledge-based Taxonomy

2. Temperature Sensors: According to (SEHRAWAT; GILL, 2019), these sensors are useful to detect physical changes in the body and objects, also measuring their thermal energy. They are also used for monitoring environmental conditions in certain locations.

Table 14. Case Study with temperature sensors

Relevant IoE dimensions and characteristics *		**Smart Sensor**		
		Govee Indoor Bluetooth Thermometer Hygrometer	Thermostat Nest Learning Google T3007ES	Temperature Sensor Google Nest T5001SF
Knowledge	Outcome	Both	Substitute	Complement

Relevant IoE dimensions and characteristics *		Smart Sensor		
		Govee Indoor Bluetooth Thermometer Hygrometer	Thermostat Nest Learning Google T3007ES	Temperature Sensor Google Nest T5001SF
	Action	Automation	Transformation	Automation
	Structure	Structured	Structured	Structured
Type	Role	Both	Both	Sensor
Capability	Communication	Device to device	Device to device	Device to device
	Processing	Edge	Cloud	Fog
	Storage	Device-level	Cluster-level	Network-level
Final Score		14 (Medium)	15 (Medium)	11 (Low)

* Dimensions selected from IoE Knowledge-based Taxonomy

3. Proximity Sensors: According to (SEHRAWAT; GILL, 2019) proximity sensors are those that detect objects or people within a certain location. There are different types of proximity sensors such as inductive, capacitive, ultrasonic, photoelectric, magnetic, etc. To classify the taxonomy, three proximity sensors with different degrees of use were selected.

Table 15. Case Study with proximity sensors

Relevant IoE dimensions and characteristics *		Smart Sensor		
		Xiaomi intelligent wireless motion detector sensor XM389BRA	Industrial Reflective Infrared Sensors E18-d80nk Arduino	AGL presence sensor
Knowledge	Outcome	Complement	Substitute	Complement
	Action	Automation	Automation	Transformation
	Structure	Structured	Structured	Structured
Type	Role	Sensor	Sensor	Both
Capability	Communication	Device to device	Device to device	Server to server
	Processing	Edge	Fog	Edge
	Storage	Network -level	Cluster-level	Network-level
Final Score		12 (Medium)	9 (low)	20 (high)

* Dimensions selected from IoE Knowledge-based Taxonomy

4. Speed sensors: According to (SEHRAWAT; GILL, 2019), speed sensors are sensors that calculate the rate of change in measuring the position of objects or people. Three-speed sensors with different degrees of use were selected.

Table 16. Case Study with Speed sensors

Relevant IoE dimensions and characteristics *		**Smart Sensor**		
		Cadence Speed Sensor Garmin Training Roller Zwift Gps Bike	24 Pulse Street Fighter Drum Speed Sensor	Bryton Smart Speed Sensor
Knowledge	Outcome	Complement	Complement	Complement
	Action	Transformation	Automation	Transformation
	Structure	Structured	Structured	Structured
Type	Role	Both	Sensor	Both
Capability	Communication	Server to server	Device to device	Server to server
	Processing	Edge	Edge	Edge
	Storage	Network -level	Cluster-level	Network-level
Final Score		12 (Medium)	9 (low)	20 (high)

* Dimensions selected from IoE Knowledge-based Taxonomy

5. Sound Sensors: The sound sensor is used to receive acoustic waves and display the sound vibration image. It usually has a built-in capacitive microphone that is sensitive to sound. The microphone vibrates with the acoustic wave, resulting in a change in capacitance and subsequent micro voltage.

Table 17. Case Study with sound sensors

Relevant IoE dimensions and characteristics *		**Smart Sensor**		
		Smart Sensor AS834+ Industrial Noise Meter Sound Level Meter Decibel Detector	Polysense sound smart sensor wxs8800-004b (30-130db range environmental indoor)	Pepperl Fuchs industrial ultrasonic sensor 24V 25-400mm
Knowledge	Outcome	Complement	Complement	Complement
	Action	Automation	Transformation	Automation
	Structure	unstructured	unstructured	unstructured
Type	Role	Sensor	Actuator	Sensor

Relevant IoE dimensions and characteristics *		**Smart Sensor**		
		Smart Sensor AS834+ Industrial Noise Meter Sound Level Meter Decibel Detector	Polysense sound smart sensor wxs8800-004b (30-130db range environmental indoor)	Pepperl Fuchs industrial ultrasonic sensor 24V 25-400mm
Capability	Communication	Device to device	Device to server	Device to device
	Processing	Edge	cloud	Edge
	Storage	Device-level	Cluster-level	Cluster-level
Final Score		11 (Low)	9 (Medium)	20 (High)

* Dimensions selected from IoE Knowledge-based Taxonomy

4.3 Quality of Service (QoS) approach for ranking knowledge in smart sensors

The IoE Integrated Knowledge Management Model, in its Second Quadrant: (Establishment (E) and Evaluation), defines that, to support the evolution of intelligent services in the IoE context, awareness of IoE Enablers is essential. And Section 3.5 presented requirements for smart sensors in IoE applications, supported by theoretical background. These requirements may be translated to evaluate the quality of intelligent services (QoS) in IoE applications.

The satisfaction of QoS requirements is critical in diverse application areas. Smart sensor nodes sense the dynamic environment in which it is deployed and gather the information for different applications such as industrial monitoring, wildlife fire tracking, agricultural monitoring, defense system (PUNDIR; SANDHU, 2021). To address the dynamic and nature of knowledge provided by smart sensors (including humans) a specific knowledge management approach is required. In this sense, the IoE Knowledge-based Taxonomy (Section 3.2) aims to identify and categorize sensors and their attributes.

The parameters of QoS in IoE applications are categorized into IoE Knowledge-based taxonomy categories goals:

- To support *Knowledge* goals: Effectivity, Interpretability, Integrity, Accuracy, and Security.

- To support Sensor's characteristic (*Type*) goal Adaptability, Usability, and Durability.

- To support *Observation* capability's goal: Mobility, Availability, Scalability, and Monitorability.

- To support Technological *Capabilities* goal: Communication efficiency, Processing efficiency, Storage Efficiency, Energy efficiency, and Maintainability.

QoS parameter is classified based on measurability (PUNDIR; SANDHU, 2021) in functional parameters (which can be measured considering a specific range) and non-functional (non-measurable parameters).

For a holistic approach, this work applied non-functional parameters of the QoS that cannot be measured using Likert-type Scales (COOK *et al.*, 2001). To provide a quantitative characterization of the intelligence in smart sensors, likert-type scales were adopted that evaluates the perceived attendance of the requirements of the smart sensor as an IoE Enabler.

As a KM System IoEDB (presented in Section 3.6) supports comparative assessments of smart sensors their strengths and weaknesses related to smartness defined.

The smart sensors collaboration in machine-to-machine (M2M) technologies are the first phase of the IoE, with collaboration and knowledge creation with human and non-human sensors collaboration to deliver automated intelligent applications. In addition, a challenge in this domain is to support the control and orchestration of intelligent sensors (things and people) embedded in smart systems. As future research, IoEDB may be used as a platform for the curation of sensors and actuators, summarized in terms of its intelligence levels as presented in Figure 51.

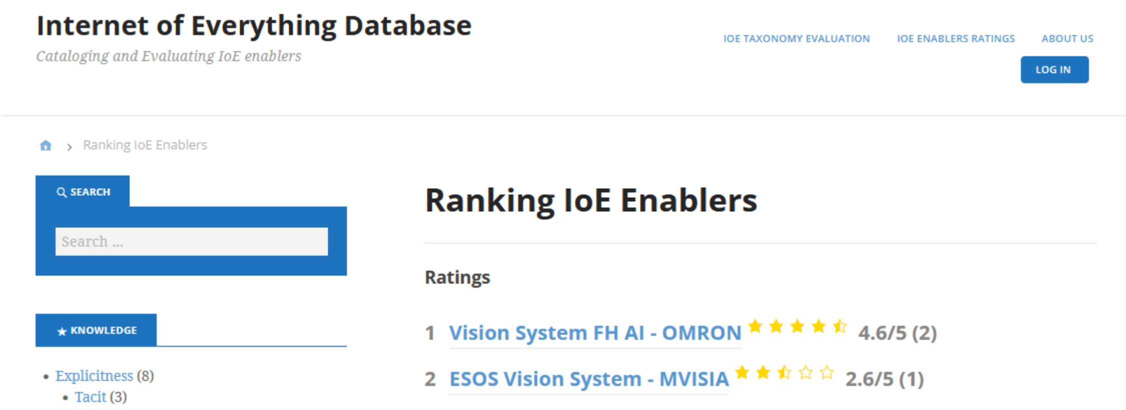


Figure 51. IoEDB Knowledge Ranking page

The IoEDB supports cataloging IoE Enablers related to smartness requirements and Communication Efficiency. The IoE Integrated Knowledge Management Model (Section 3.4) presented the approach for the evaluation of the Interoperability Maturity Assessment (IMA) that is the ability to exchange and use information during internalization (support self-learning) and combination of knowledge in H2H, M2H, and M2M interactions.

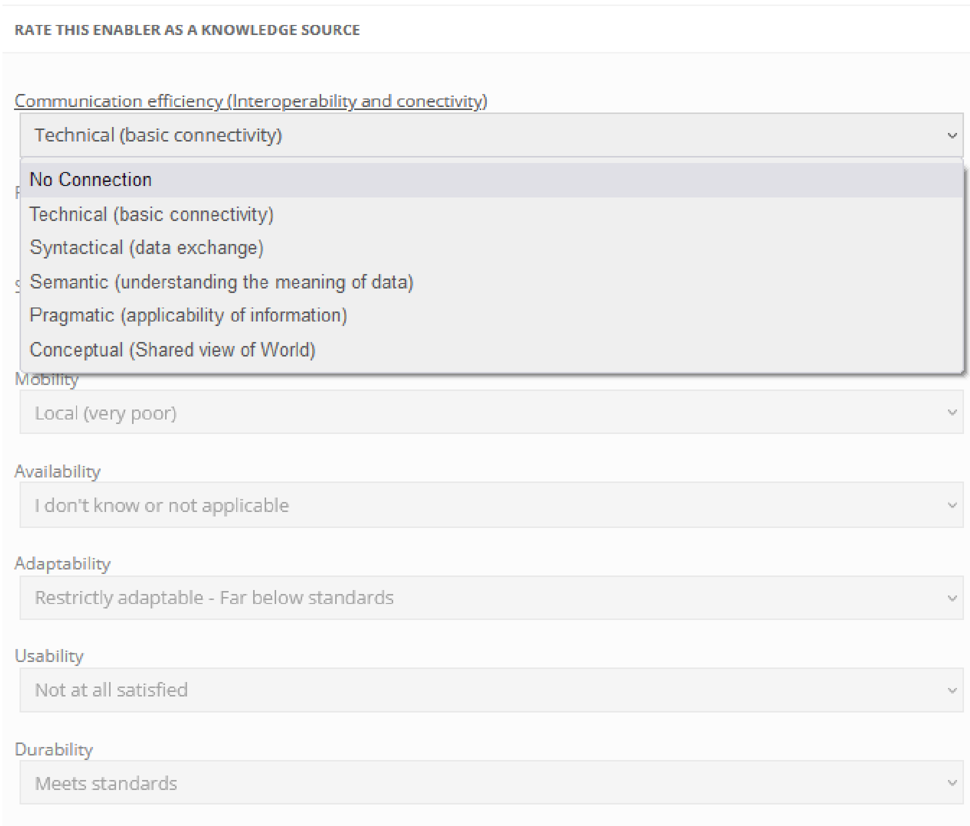


Figure 52. Ranking knowledge of IoE Enablers

4.4 Planning IoE Integrated Knowledge Management Model evaluation

In preparing for digitalization, the Brazilian government issued the Brazilian Digital Transformation Strategy (E-Digital), the strategy coordinates different governmental initiatives to further the digitalization process to enable economic growth and societal benefits (MCTIC, 2018). In the military field, digital government strategy regards Defense Preparation Transformation of public services offered by the Army, Navy, and Air Force (SCHEDLER; GUENDUEZ; FRISCHKNECHT, 2019). During peace, crisis, or conflict situations, intelligence activity is crucial to assist the decision-making process of political and military authorities and support the planning and conduct of military operations (BRASIL - ESTADO-MAIOR CONJUNTO DAS FORÇAS ARMADAS, 2020) necessary for the global age dynamics (FARIAS; OLIVEIRA; SOUZA, 2009). IoE applications support intelligence activities and situational awareness in military operations. The use of intelligent sensors (things and humans) and data analysis enhances the intelligence scenario and supports decisive actions to influence operations. To support knowledge acquisition plans of military intelligent services during situations of peace (SCHEDLER; GUENDUEZ; FRISCHKNECHT, 2019), this work analyzed how military IoE applications should benefit from the collaborative classification of IoE enablers, using the IoE knowledge-based taxonomy (FARIAS DA COSTA; OLIVEIRA; DE SOUZA, 2021) in the IoE Database, and from a IoE KM strategy supported by the proposed IoE Integrated Knowledge Management Model.

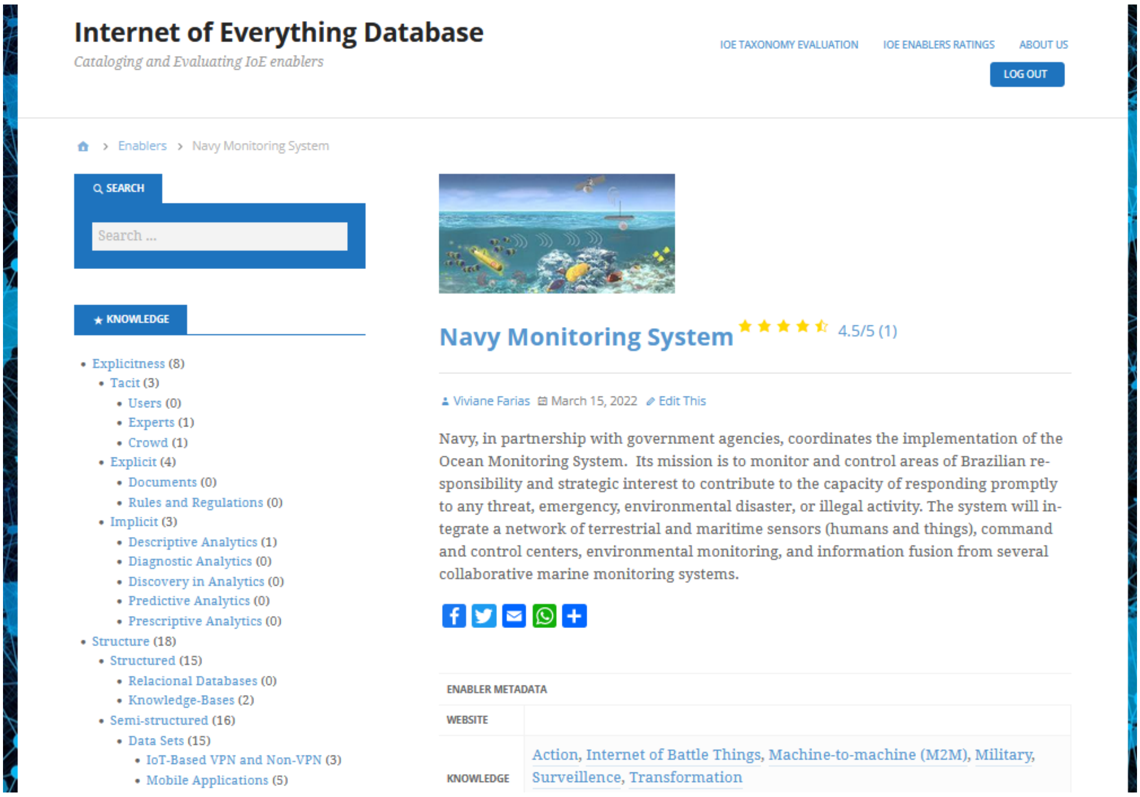


Figure 53. IoE Monitoring System

IoE Integrated KM Model applied in a military context

As a fictitious case study, this section will consider that the Brazilian Navy, in partnership with government agencies, coordinates the implementation of the Ocean Monitoring System. The referred system was selected as an example and case study because Monitoring Systems are tools for governance that contribute to developing technological capabilities for societal benefit and value co-creation. The information is used in this case study is available at IoEDB (https://ioe.cos.ufrj.br/?enablers=navy-monitoring-system). The IoE System will integrate a network of terrestrial and maritime sensors (humans and things), command and control centers, environmental monitoring, and information fusion from several collaborative marine monitoring systems.

Knowledge Management in military operations is paramount (FARIAS; OLIVEIRA; SOUZA, 2009). In this context, Servitization (with Serendipity focus) applied to the Monitoring System is a business model in which collaborative marine monitoring systems (providers) deliver their products as services, in this case, especially intelligent services (GOBBLE, 2018), and may benefit from serendipitous M2M and H2M interactions. For instance, when sensors are used to transmit environmental data from a marine monitoring system, that is digitization. When that transmitted data is used to respond promptly to any threat or environmental disaster and improve the Navy mission to monitor and control areas of Brazilian responsibility, it is digitalization. So Servitization is an operational model powered by digitalization (in IoE) and knowledge management.

Reinforcement (R) and Governance in IoE come from the allocation of decision control to guide and organize the intelligent service activities. It defines the regulatory context that includes social competencies and technological capabilities to institutionalize service systemic evolution. Governance for digitalization in military activities is integrated and supported by the reference model for the decision-making process in military command and control (C^2), which integrates intelligence and decision to ensure the coherence of the action-oriented outcomes (BRASIL - ESTADO-MAIOR CONJUNTO DAS FORÇAS ARMADAS, 2020).

Intelligence activity for joint operations that combine Army, Navy, and Air Force (BRASIL - ESTADO-MAIOR CONJUNTO DAS FORÇAS ARMADAS, 2020) adopts an Intelligence Cycle, called the OODA (Observe, Orient, Decide, Act) loop.

The IoEDB as a platform for curation and cataloging of IoE Enablers may support command and control centers in awareness of resources available in the IoE context. Especially during the military observation phase of the OODA cycle, IoEDB may support operation planning providing a collaborative classification of knowledge sources: the network of terrestrial and maritime sensors (humans and things), their observations capabilities, and technology resources and trends.

Additionally, to validate conceptually the IoE Integrated KM Model proposed in this work, the benefits of the proposed service evolution approach were analyzed to support intelligent services in military joint forces activities. The intelligence activities of the military (C^2) consist of intelligent services centered on intangible elements, so the IoE Integrated KM cycle starts from the second quadrant, Establishment (E), and supports the military (C^2) OODA loop as follows:

- *Observe*: Refers to Intelligence Establishment through knowledge internalization and learning. In the IoE context, joint operation planning regards artificial intelligence system and their relationships with human sensors. Intelligence enablers are sources and systems used to observe, perceive, and transmit information about conditions, situations, and events, which will allow the acquisition of critical knowledge to the Operations Command. It refers to First Quadrant: Servitization (S) and Serendipity

- *Orient*: Refers to Intelligence Reinforcement through knowledge socialization. Intelligence Needs (IN) are knowledge gaps that clarify the uncertainties that may influence the decision-making process. Intelligence must be supported by integrating all sources in the knowledge production process through the Knowledge Acquisition Plan (KAP) (OURIQUES *et al.*, 2019)(BRASIL - ESTADO-MAIOR CONJUNTO DAS FORÇAS ARMADAS, 2020). It refers to Second Quadrant: Establishment (E) and Evaluation

- *Decide*: Refers to Intelligence Infrastructure through knowledge externalization to minimize or eliminate uncertainties that involve any decision-making process. Joint forces must develop actions under permanent monitoring and systematic exploration. The intelligence activity must have a governance committee to guide the codification of conventional rules aligned with implicit shared values (PITT; OBER; DIACONESCU, 2017). It refers to the Third Quadrant: Reinforcement (R) and Governance.

- *Act*: Refers to preparing technological infrastructure for intelligent service delivery (Servitization) and knowledge combination where collective action is composed of collective decision (knowledge aggregation), collective coordination (knowledge alignment), and collective memory (knowledge codification). The focus is on acting intelligently in terms of an ideal performance called rationality. So AI acts to achieve the best result or uncertainty, the best-expected result (PASCHEN; KIETZMANN; KIETZMANN, 2019) combined with human intelligence. Fourth Quadrant: Infrastructure (I) and Technology.

In an attempt to offer some preliminary validation for the practicality of this model, a qualitative methodological approach to understanding how IoE enablers are utilized by Monitoring System designers /employees/customers/ managers and how the knowledge obtained from it creates value in the IoE context. By applying concepts that are deeply rooted in knowledge management literature, the intention was to focus on the phenomenon rather than constructs or variables.

In the evaluation emphasizes the application of the IoE Integrated KM Model in IoE to derive actionable knowledge from it.

Table 18. IoE Integrated KM Model case study

Service Cycle Process	IoE Knowledge Enabler or Assets	Knowledge Process	Interoperability Maturity Assessment (IMA)	Contextual recommended activities
Servitization (S) And Serendipity	**Tacit**: Society and military human sensors **Explicit**: Plans, Rules, Regulations, and Data Sources Environmental data from a marine monitoring system **Implicit**: Intelligent sensors (things) and Data analysis Analysis of situational awareness in military operations	**Combination** H2M and M2M knowledge flows **Internalization**: Machine Learning. Self-learning and Organizational Learning	The ability of IoE Enablers to exchange and use information : 2	**Acquisition** Acquisition of critical knowledge to the Operations Command. Instrumentation intelligence due to IoT based, military sensor networks and the semantic web, Enable smart systems to socialize with the user and understand its social context. Analyze big data generated by IoT devices as a rich source of the user's context. Analyze generated social data to achieve collective intelligence (eg. using joint military operations) Maintain context-awareness in joint operations considering social relationships in M2M and H2M interactions. Maintain context-awareness of infrastructure capabilities as well as information semantic perspective. **Utilization**. Sources and systems used to observe, perceive, and transmit information about conditions, situations, and events Transmitted data is used to respond promptly to any threat or environmental disaster and improve the Navy mission providing real-time information Data from alerts and forecasts, Personalized services and customized content according to the operation's social context. Use of artificial social agents to generate and manage actionable knowledge within the IoE environment. Allow devices in the execution of automatic tasks without the involvement of the humans Support collaboration and cooperation between IoE devices and interoperability of services on behalf of the humans. Interact with big data tools and other analytical software to gain the experience **Learning** Support flexibility of learning and knowledge. Cultivate processes of meta-learning (learning how to learn) Allow sensors and actuators to take advantage of knowledge and experience to perceive and interact with the IoE environment. Cultivate learn by doing (related to sensors and actuators environment) Support domain adaptation to allow models to be trained over exhaustive datasets of a dynamic environment Support end-to-end learning approaches to train the decision-making pipeline from perception to action

Service Cycle Process	IoE Knowledge Enabler or Assets	Knowledge Process	Interoperability Maturity Assessment (IMA)	Contextual recommended activities
Establishment (E) And Evaluation	**Tacit**: Command and control centers intelligent sensors (humans) **Explicit**: Joint operation planning Plans, Rules, Regulations, and Data Sources **Implicit**: Intelligent sensors (things) Data analysis Analysis of situational awareness in military operations	**Internalization** Machine Learning. Self-learning and Military training operations **Socialization** Artificial intelligence systems Network of terrestrial and maritime sensors (humans and things) Joint Operation Centers	The ability of IoE Enablers to exchange and use information: 2	**Identification** intelligence Orchestration Maintain context-awareness and record the resulting interactions through learning by doing. Understand environment monitoring context's semantic and customize the services and applications accordingly. Identify potential M2M and M2P interactions in the monitoring environment (physical or cyberspace) **Evaluation** Maximize the system knowledge about the social dimension of the users and machines. Maximize context-awareness of knowledge in IoE applications, computational capability perspective as well as information semantic reasoning perspective. Support knowledge acquisition plans of military intelligent services, through environmental monitoring Integrate knowledge tasks that are distributed among the population, the institutions, and infrastructures Support partnership with government agencies and coordinates the implementation of joint monitoring Support information fusion from several collaborative marine monitoring systems. Plan military operations

Service Cycle Process	IoE Knowledge Enabler or Assets	Knowledge Process	Interoperability Maturity Assessment (IMA)	Contextual recommended activities
Reinforcement (R) and Governance	**Tacit**: Command and control centers Intelligent sensors (humans) The joint forces governance committee **Explicit**: Joint operation planning Plans, Rules, Regulations, and Data Sources Knowledge Acquisition Plan (KAP) **Implicit**: Intelligent sensors (things) Data analysis Analysis of situational awareness in military operations	**Externalization** Knowledge Acquisition Plan (KAP) Joint operation planning Plans, Rules, Regulations, and Data Sources Curation of a live knowledge network of IoE Enablers **Socialization** Artificial intelligence systems Network of terrestrial and maritime sensors (humans and things) Joint Operation Centers	The ability of IoE Enablers to exchange and use information: 2	**Update** Intelligence Empowerment Create a social relationship network between sensors and actuators (M2M, H2M, H2H). Support a live knowledge network, as the observed nodes' activities and profiles change over time due to IoE environment dynamics. Develop machines’ thinking abilities side-by-side with their social integration abilities. Maintain tight coupling of AI techniques merged with the humans´ and machines’ social context. Cultivate a serendipitous environment through the collaboration of IoE devices. **Protection** Improvements of human skills (military, joint forces, and society) and know-how to minimize or eliminate uncertainties that involve any decision-making process Evaluate the trust level of IoE sensors (human and machines) and IoE applications and infer the reliability among devices. Implement a social privacy preserving scheme to support trust. Protect sensitive information to support the customization of offered services. Provide a knowledge protection strategy on behalf of critical knowledge identified for IoE applications. **Governance** Support a governance strategy and control to leverage intelligent connections in IoE applications Maintain awareness of governance paradox and promote service innovation Define governance directives to support an evolving degree of reconfiguration of roles and responsibilities based on the codification of conventional rules aligned with implicit shared values

Service Cycle Process	IoE Knowledge Enabler or Assets	Knowledge Process	Interoperability Maturity Assessment (IMA)	Contextual recommended activities
Infrastructure (I) And technology	**Tacit**: Command and control centers Intelligent sensors (humans) The joint forces governance committee **Explicit**: Joint operation planning Plans, Rules, Regulations, and Data Sources Knowledge Acquisition Plan (KAP) **Implicit**: Intelligent sensors (things) Data analysis Analysis of situational awareness in military operations	**Externalization** Knowledge Acquisition Plan (KAP) Joint operation planning Plans, Rules, Regulations, and Data Sources Curation of a live knowledge network of IoE Enablers **Combination** H2M and M2M knowledge flows	The ability of IoE Enablers to exchange and use information: 2	**Storage** Support data management activities at the unit IoT level, involving pre-processing and filtering tasks, such as data aggregation and data compression. Support IoT sensor data acquisition IoT and complements it with external data such as open linked data and knowledge graphs or codified knowledge from data sources **Transfer** Support social networks and IoT to the scalability of interconnected sensors and actuators. Support service recommendation system to leverage the social relationships and serendipity in IoE interactions (M2M, H2M and H2H). Support a social connected community of sensors and actuators Integrate communication and processing technologies near end-user devices Improve the network performance, reducing unnecessary network traffic and increasing the throughput Provide state-of-the-art technologies, software, databases, and repositories acting intelligently in terms of an ideal performance called rationality

5 Conclusion

Nevertheless, to entirely understand the transformative potential of collaboration between people and things in IoE applications, this thesis addressed the research gap of defining a KM strategy to support people and machine knowledge flows towards IoE value creation and intelligent services. This work contributes to the development of a knowledge-based taxonomy related to IoE applications, which will guide both interested researchers in this field, as well as application developers, in the design of knowledge-intensive IoE services. The proposed taxonomy is extendable: it allows for the inclusion of additional dimensions and new characteristics within the IoE paradigm and other emerging paradigms under the IoE umbrella or concerned with intelligent network connections. Thus, I believe there is still significant room for future research and work on this topic.

The main contributions are (i) a novel knowledge-based IoE taxonomy which provided guidelines and a comprehensive overview of the topic, (ii) the proposition of a platform to conduct distributed and standardized curation of IoE initiatives capable and allowing the collaborative evolution of the dynamic IoE knowledge-based taxonomy; (iii) development of the IoE Integrated Knowledge Management Model to address specificities of IoE KM, (iv) expanding the awareness about IoE enablers through a knowledge base focused on this topic, this thesis presented intelligence requirements for smart sensors so that it supports qualitative evaluation of smart sensors intelligence.

The goal of this thesis is to contribute to value creation in the adoption of IoE applications by developing a model that allows the knowledge identification of IoE Enablers regarding intelligence and efficiency in supporting the IoE lifestyle.

5.1 Reviving research questions

The trajectory of the research for the thesis started with a comprehensive exploration of the Internet of Everything paradigm and related challenges.

My interest in KM research started back in my master's degree thesis about knowledge management applied to organizations. At that time, the challenge was to drive knowledge creation and learning through a knowledge management strategy with a focus on learning and knowledge sharing in human-to-human interactions.

Since then, challenges with the advent of the Internet of Thing are much more than just about connecting the unconnected and using things on behalf of humans. But the Internet of Everything challenge presents a new era, where things are self-governing without human intervention. I identified research gaps in modeling knowledge sharing between people and things for knowledge creation. Where self-* behavior of humans and machines will drive serendipitous opportunities for knowledge creation, and a KM strategy will support conducting service evolution and improvement. This exploration of the IoE paradigm and my background in knowledge management made me decide that the best contribution that I could give in this field of research would be to address machine knowledge management and human to machine knowledge flows, coping with the impact and benefiting from the IoE Lifestyle.

RQ1: How to apply knowledge management strategy in the context of IoE with a focus on collective intelligence and knowledge flows between M2M, H2H, and M2H interactions?

This work contributes to IoE KM research, with the development of the IoE Integrated KM Model that addresses KM research and Service Science on behalf of an IoE KM strategy for intelligent services evolution and human and machine KM.

RQ2: How to promote service enhancement and evolution in the IoE context to deliver greater value to connected society?

This work contributes to the development of a Knowledge-based Taxonomy to provide awareness of IoE applications, support machine knowledge management and the design of knowledge-intensive IoE services.

RQ3: How to identify and evaluate (rank) knowledge sources in the IoE context?

This thesis presented smart sensors requirements in IoE applications, supported by theoretical background. These requirements may be used to evaluate the quality of intelligent services (QoS) in IoE applications.

5.2 Limitations

The work presented in this thesis is limited because it needs to go beyond the creation of the proposed artifacts (The Knowledge-based taxonomy, The IoE Integrated KM Model, and IoE Database) to track their practical applicability in real IoE use cases.

Regarding the evaluation of intelligent requirements for smart sensors, it can be considered a limitation of the fact that some of the work in the methodology, such as the evaluation of the degree of intelligence considered a simple scale. This limitation was mitigated by the effort of the author to go beyond this research field and validate the artifacts evaluation in IoE and IoE relevant publications and forums.

5.3 Publications and Future works

Table 19 complements the contributions mentioned above, listing the publications that were accepted or submitted during the period of production of this thesis, and that is directly related to this research.

Table 19. Publications

#	Title	Fórum	Status
1	Internet of Everything (IoE) Taxonomies: A Survey and a Novel Knowledge-based Taxonomy	MDPI Sensors 2021	Published
2	Towards a taxonomy for ranking knowledge in Internet of Everything	CSCWD 2021	Published
3	A collaborative approach to support interoperability and awareness of the Internet of Everything (IoE) enablers	ICHMS 2021	Published
4	Relatório Técnico: Internet of Everything (IoE) Taxonomy	PESC Publications	Published
5	Internet of Everything (IoE) Taxonomies	Scholarly Com. Encyclopedia	Published
6	An approach for intelligence evaluation in smart sensors	CSCWD 2022	Accepted
7	Smart Sensors for the Internet of Everything (IoE): A Survey	MDPI Sensors 2022	Ready to submit

References

ABBAS, N. *et al.* Mobile Edge Computing: A Survey. **IEEE Internet of Things Journal**, v. 5, n. 1, p. 450–465, 2018.

ABBAS, S. S. A.; PRIYA, K. L. **Self Configurations, Optimization and Protection Scenarios with wireless sensor networks in IIoT**. 2019 International Conference on Communication and Signal Processing (ICCSP). **Anais**...abr. 2019.

ABDEL-BASSET, M. *et al.* Deep learning for Heterogeneous Human Activity Recognition in Complex IoT Applications. **IEEE Internet of Things Journal**, 2020.

ABDUL-GHANI, H. A.; KONSTANTAS, D.; MAHYOUB, M. A Comprehensive IoT Attacks Survey based on a Building-blocked Reference Model. **International Journal of Advanced Computer Science and Applications (IJACSA)**, v. 9, n. 3, 2018.

ABEBE, M. A. *et al.* **A General Multimedia Representation Space Model toward Event-Based Collective Knowledge Management**. Proceedings - 19th IEEE International Conference on Computational Science and Engineering. **Anais**...2017. Disponível em: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85026675326&doi=10.1109%2fCSE-EUC-DCABES.2016.234&partnerID=40&md5=81da838e898b4d5afa455f35c9ea1b5b>

ABRISHAMBAF, R. **Structural Modeling and Implementation of Smart Sensor and Actuator Networks using IEEE 1451**. 2020 IEEE International Instrumentation and Measurement Technology Conference (I2MTC). **Anais**... Em: 2020 IEEE INTERNATIONAL INSTRUMENTATION AND MEASUREMENT TECHNOLOGY CONFERENCE (I2MTC). maio 2020.

ACKOFF, R. From data to wisdom. **Journal of applied systems analysis**, 1989.

AGARWAL, R. et al. **Unified IoT ontology to enable interoperability and federation of testbeds**. IEEE 3rd World Forum on Internet of Things (WF-IoT). **Anais**... Em: IEEE 3RD WORLD FORUM ON INTERNET OF THINGS (WF-IOT). Reston, VA, USA: 12 dez. 2016.

AHAD, A.; TAHIR, M.; YAU, K.-L. A. 5G-Based Smart Healthcare Network: Architecture, Taxonomy, Challenges and Future Research Directions. **IEEE Access**, v. 7, p. 100747–100762, 2019.

AHELEROFF, S. et al. IoT-enabled smart appliances under industry 4.0: A case study. **Advanced Engineering Informatics**, v. 43, 2020.

AHMED, E. et al. Internet-of-things-based smart environments: state of the art, taxonomy, and open research challenges. **IEEE Wireless Communications**, v. 23, n. 5, p. 10–16, out. 2016.

AHMED, I. et al. Exploring Deep Learning Models for Overhead View Multiple Object Detection. **IEEE Internet of Things Journal**, v. 7, n. 7, p. 5737–5744, 2020.

AHMED, M. et al. IoT Data Qualification for a Logistic Chain Traceability Smart Contract. **Sensors**, v. 21, n. 6, p. 2239, 23 mar. 2021.

AKHTER, F. et al. Iot enabled intelligent sensor node for smart city: Pedestrian counting and ambient monitoring. **Sensors (Switzerland)**, v. 19, n. 15, 2019.

AKMANDOR, A. O.; YIN, H.; JHA, N. K. Smart, Secure, Yet Energy-Efficient, Internet-of-Things Sensors. **IEEE Transactions on Multi-Scale Computing Systems**, v. 4, n. 4, p. 914–930, 2018.

AKOKA, J.; COMYN-WATTIAU, I.; LAOUFI, N. Research on Big Data – A systematic mapping study. **Computer Standards & Interfaces**, v. 54, p. 105–115, 1 nov. 2017.

ALAHI, M. E. E.; MUKHOPADHYAY, S. C. Conclusion and Future Work. **Smart Sensors, Measurement and Instrumentation**, v. 35, p. 131–132, 2019.

ALAVI, A. H. et al. Internet of Things-enabled smart cities: State-of-the-art and future trends. **Measurement**, v. 129, p. 589–606, 2018.

AL-EMRAN, M. et al. The impact of knowledge management processes on information systems: A systematic review. **International Journal of Information Management**, v. 43, p. 173–187, 2018.

ALKHABBAS, F.; SPALAZZESE, R.; DAVIDSSON, P. Characterizing Internet of Things Systems through Taxonomies: A Systematic Mapping Study. **Internet of Things**, v. 7, p. 100084, set. 2019.

ALONSO, M. et al. Smart Sensors for Smart Grid Reliability. **Sensors**, v. 20, n. 8, p. 2187, jan. 2020a.

ALONSO, M. et al. Smart Sensors for Smart Grid Reliability. **Sensors**, v. 20, n. 8, p. 2187, jan. 2020b.

AL-QURISHI, M. et al. **A Framework of Knowledge Management as a Service over Cloud Computing Platform**. Proceedings of the International Conference on Intelligent Information Processing, Security and Advanced Communication. **Anais**...: IPAC ’15.New York, NY, USA: Association for Computing Machinery, 2015. Disponível em: <https://doi-org.ez29.periodicos.capes.gov.br/10.1145/2816839.2816908>

ALSAMANI, B.; LAHZA, H. **A taxonomy of IoT: Security and privacy threats**. 2018 International Conference on Information and Computer Technologies (ICICT). **Anais**... Em: 2018 INTERNATIONAL CONFERENCE ON INFORMATION AND COMPUTER TECHNOLOGIES (ICICT). DeKalb, IL: IEEE, mar. 2018. Disponível em: <https://ieeexplore.ieee.org/document/8356843/>. Acesso em: 25 out. 2019

ALSHAMSI, A. et al. **Monitoring pollution: Applying IoT to create a smart environment**. 2017 International Conference on Electrical and Computing

Technologies and Applications (ICECTA). **Anais**... Em: 2017 INTERNATIONAL CONFERENCE ON ELECTRICAL AND COMPUTING TECHNOLOGIES AND APPLICATIONS (ICECTA). Ras Al Khaimah: IEEE, nov. 2017. Disponível em: <http://ieeexplore.ieee.org/document/8251998/>. Acesso em: 24 out. 2019

ALTURKI, A.; GABLE, G. G.; BANDARA, W. **A Design Science Research Roadmap**. (H. Jain, A. P. Sinha, P. Vitharana, Eds.)Service-Oriented Perspectives in Design Science Research. **Anais**...: Lecture Notes in Computer Science.Berlin, Heidelberg: Springer, 2011.

ANASTASIOU, D. et al. **The Role of the Human User in the Cognitive Internet of Things**. Proceedings of the 8th International Conference on Human-Agent Interaction. **Anais**... Em: HAI ’20: 8TH INTERNATIONAL CONFERENCE ON HUMAN-AGENT INTERACTION. Virtual Event USA: ACM, 10 nov. 2020. Disponível em: <https://dl.acm.org/doi/10.1145/3406499.3418762>. Acesso em: 25 ago. 2021

ANG, K. L.-M.; SENG, J. K. P. Application Specific Internet of Things (ASIoTs): Taxonomy, Applications, Use Case and Future Directions. **IEEE Access**, v. 7, p. 56577–56590, 2019.

ANTENUCCI, A. et al. **An Industrial Distributed Network of Intelligent Robotic Security Guards Based on the Internet of Robotic Things Paradigm**. 2021 International Conference on Computer, Control and Robotics (ICCCR). **Anais**... Em: 2021 INTERNATIONAL CONFERENCE ON COMPUTER, CONTROL AND ROBOTICS (ICCCR). jan. 2021.

ARDITO, L.; D’ADDA, D.; MESSENI PETRUZZELLI, A. Mapping innovation dynamics in the Internet of Things domain: Evidence from patent analysis. **Technological Forecasting and Social Change**, maio 2017.

ARMANDO, N. et al. An Outlook on Physical and Virtual Sensors for a Socially Interactive Internet. **Sensors**, v. 18, n. 8, p. 2578, ago. 2018.

ASGHARI, P.; RAHMANI, A. M.; JAVADI, H. H. S. Service composition approaches in IoT: A systematic review. **Journal of Network and Computer Applications**, v. 120, p. 61–77, 15 out. 2018.

ASGHARI, P.; RAHMANI, A. M.; JAVADI, H. H. S. Internet of Things applications: A systematic review. **Computer Networks**, v. 148, p. 241–261, 15 jan. 2019.

ASHRAF, Q. M.; HABAEBI, M. H. Autonomic schemes for threat mitigation in Internet of Things. **Journal of Network and Computer Applications**, v. 49, p. 112–127, 1 mar. 2015.

ASLAM, S.; MICHAELIDES, M. P.; HERODOTOU, H. Internet of Ships: A Survey on Architectures, Emerging Applications, and Challenges. **IEEE Internet of Things Journal**, v. 7, n. 10, p. 9714–9727, out. 2020.

ASTILL, J. et al. Smart poultry management: Smart sensors, big data, and the internet of things. **Computers and Electronics in Agriculture**, v. 170, 2020.

ATAT, R. et al. Big Data Meet Cyber-Physical Systems: A Panoramic Survey. **IEEE Access**, v. 6, p. 73603–73636, 2018.

ATZORI, L.; IERA, A.; MORABITO, G. Understanding the Internet of Things: definition, potentials, and societal role of a fast evolving paradigm. **Ad Hoc Networks**, v. 56, p. 122–140, mar. 2017.

AUGER, A.; EXPOSITO, E.; LOCHIN, E. **Towards the internet of everything: Deployment scenarios for a QoO-aware integration platform**. IEEE 4th World Forum on Internet of Things (WF-IoT). **Anais**... Em: 2018 IEEE 4TH WORLD FORUM ON INTERNET OF THINGS (WF-IOT). Singapore: IEEE, 5 fev. 2018. Disponível em: <https://ieeexplore.ieee.org/document/8355113/>. Acesso em: 27 ago. 2020

AZAD, M. A. et al. Privacy-preserving Crowd-sensed Trust Aggregation in the User-centeric Internet of People Networks. **ACM Transactions on Cyber-Physical Systems**, v. 5, n. 1, p. 1–24, 21 jan. 2021.

BABAOGLU, O. et al. The self-star vision. Em: **Self-star Properties in Complex Information Systems: conceptual and Practical Foundations**. Berlin, Heidelberg: Springer-Verlag, 2005. p. 1–20.

BACCIU, D. et al. **On the need of machine learning as a service for the internet of things**. ACM International Conference Proceeding Series. **Anais**...2017. Disponível em: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85044430813&doi=10.1145%2f3109761.3109783&partnerID=40&md5=9ec30b895b10ee98f2b792d9c2a2bf14>

BAJAJ, G. et al. 4W1H in IoT Semantics. **IEEE Access**, v. 6, p. 65488–65506, 2018.

BALCO, P.; DRAHOOVÁ, M. **Knowledge Management as a Service (KMaaS)**. 2016 IEEE 4th International Conference on Future Internet of Things and Cloud Workshops (FiCloudW). **Anais**...2016.

BAMGBOYE, O.; LIU, X.; CRUICKSHANK, P. **Towards Modelling and Reasoning About Uncertain Data of Sensor Measurements for Decision Support in Smart Spaces**. IEEE 42nd Annual Computer Software and Applications Conference (COMPSAC). **Anais**... Em: IEEE 42ND ANNUAL COMPUTER SOFTWARE AND APPLICATIONS CONFERENCE (COMPSAC). Tokyo, Japan: 23 jul. 2018.

BANSAL, S.; KUMAR, D. IoT Ecosystem: A Survey on Devices, Gateways, Operating Systems, Middleware and Communication. **International Journal of Wireless Information Networks**, v. 27, n. 3, p. 340–364, set. 2020.

BAOCHENG, W.; SHAN, L. The Research of Security in NB-IoT. **EITCE - Xiamen, China**, p. 5, 2020.

BARKER, L. et al. **Taxonomy for Internet of Things - Tools for Monitoring Personal Effects**. International Conference on Pervasive and Embedded Computing and Communication Systems (PECCS 2014). **Anais**... Em: INTERNATIONAL CONFERENCE ON PERVASIVE AND EMBEDDED COMPUTING AND COMMUNICATION SYSTEMS (PECCS 2014). Lisbon, Portugal: 7 jan. 2014.

BARNAGHI, P. et al. Semantics for the Internet of Things: Early Progress and Back to the Future. **International Journal on Semantic Web and Information Systems (IJSWIS)**, v. 8, n. 1, p. 1–21, 1 jan. 2012.

BASKERVILLE, R.; PRIES-HEJE, J.; VENABLE, J. **Soft design science methodology**. Proceedings of the 4th International Conference on Design Science Research in Information Systems and Technology - DESRIST ’09. **Anais**... Em: THE 4TH INTERNATIONAL CONFERENCE. Philadelphia, Pennsylvania: ACM Press, 2009. Disponível em: <http://portal.acm.org/citation.cfm?doid=1555619.1555631>. Acesso em: 27 ago. 2018

BELLAVISTA, P.; BERROCAL, J. A survey on fog computing for the Internet of Things. **Pervasive and Mobile Computing**, v. 52, p. 71–99, 1 jan. 2019.

BENNARA, M. et al. **Interoperability of Semantically-Enabled Web Services on the WoT: Challenges and Prospects**. Proceedings of the 22nd International Conference on Information Integration and Web-based Applications & Services. **Anais**... Em: IIWAS ’20: THE 22ND INTERNATIONAL CONFERENCE ON INFORMATION INTEGRATION AND WEB-BASED APPLICATIONS & SERVICES. Chiang Mai Thailand: ACM, 30 nov. 2020. Disponível em: <https://dl.acm.org/doi/10.1145/3428757.3429199>. Acesso em: 25 ago. 2021

BERGER, S.; DENNER, M.-S.; RÖGLINGER, M. **The Nature of Digital Technologies – Development of a Multi-layer Taxonomy**. Twenty-Sixth European Conference on Information Systems (ECIS2018). **Anais**... Em: TWENTY-SIXTH EUROPEAN CONFERENCE ON INFORMATION SYSTEMS (ECIS2018). Portsmouth,UK: 23 jun. 2018.

BERTOLI, A. et al. Smart Node Networks Orchestration: A New E2E Approach for Analysis and Design for Agile 4.0 Implementation. **Sensors**, v. 21, n. 5, p. 1624, 26 fev. 2021.

BHATT, S.; PATWA, F.; SANDHU, R. **An Access Control Framework for Cloud-Enabled Wearable Internet of Things**. IEEE 3rd International Conference on Collaboration and Internet Computing (CIC). **Anais**... Em: IEEE 3RD INTERNATIONAL CONFERENCE ON COLLABORATION AND INTERNET COMPUTING (CIC). San Jose, CA, USA: out. 2017.

BISDIKIAN, C.; KAPLAN, L. M.; SRIVASTAVA, M. B. On the Quality and Value of Information in Sensor Networks. **ACM Trans. Sen. Netw.**, v. 9, n. 4, p. 1–26, jul. 2013.

BJÖRNEBORN, L. Three key affordances for serendipity: Toward a framework connecting environmental and personal factors in serendipitous encounters. **Journal of Documentation**, v. 73, n. 5, p. 1053–1081, 2017.

BOJANOVA, I.; HURLBURT, G.; VOAS, J. Imagineering an Internet of Anything. **Computer - IEEE Computer Society**, v. 47, n. 6, p. 72–77, jun. 2014.

BONTE, P. et al. **C-Sprite: Efficient Hierarchical Reasoning for Rapid RDF Stream Processing**. Proceedings of the 13th ACM International Conference on Distributed and Event-based Systems - DEBS ’19. **Anais**... Em: THE 13TH ACM INTERNATIONAL CONFERENCE ON DISTRIBUTED AND EVENT-BASED SYSTEMS—DEBS ’19.

Darmstadt, Germany: ACM Press, 24 jun. 2019. Disponível em: <http://dl.acm.org/citation.cfm?doid=3328905.3329502>. Acesso em: 18 nov. 2019

BOTTA, A. et al. Integration of Cloud computing and Internet of Things: A survey. **Future Generation Computer Systems**, v. 56, p. 684–700, 1 mar. 2016.

BOYES, H. et al. The industrial internet of things (IIoT): An analysis framework. **Computers in Industry**, v. 101, p. 1–12, 1 out. 2018.

BRASIL - ESTADO-MAIOR CONJUNTO DAS FORÇAS ARMADAS. **Doutrina de Operações Conjuntas (MD30-M-01)**Ministério da Defesa, , 2020. Disponível em: <https://www.gov.br/defesa/pt-br/arquivos/legislacao/emcfa/publicacoes/doutrina/md30-m-01-vol-1-2a-edicao-2020-dou-178-de-15-set.pdf>. Acesso em: 15 mar. 2021

BUGEJA, J.; DAVIDSSON, P.; JACOBSSON, A. **Functional Classification and Quantitative Analysis of Smart Connected Home Devices**. Global Internet of Things Summit (GIoTS). **Anais**... Em: GLOBAL INTERNET OF THINGS SUMMIT (GIOTS). Bilbao, Spain: 4 jun. 2018.

BUSACCA, F. et al. **An experimental testbed of an Internet of Underwater Things**. Proceedings of the 14th International Workshop on Wireless Network Testbeds, Experimental evaluation & Characterization. **Anais**... Em: MOBICOM ’20: THE 26TH ANNUAL INTERNATIONAL CONFERENCE ON MOBILE COMPUTING AND NETWORKING. London United Kingdom: ACM, 21 set. 2020. Disponível em: <https://dl.acm.org/doi/10.1145/3411276.3412186>. Acesso em: 25 ago. 2021

CABRA, J. et al. **An IoT approach for wireless sensor networks applied to e-health environmental monitoring**. Proceedings - 2017 IEEE International Conference on Internet of Things, IEEE Green Computing and Communications, IEEE Cyber, Physical and Social Computing, IEEE Smart Data, iThings-GreenCom-CPSCom-SmartData 2017. **Anais**...2018. Disponível em: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85047427358&doi=10.1109%2fiThings-GreenCom-CPSCom-SmartData.2017.91&partnerID=40&md5=64b1b8ca6834c695d53f223692f200d1>

CAI, S. et al. Data aggregation processes: a survey, a taxonomy, and design guidelines. **Computing**, p. 1–33, 2018.

CHANAL, P. M.; KAKKASAGERI, M. S. Security and Privacy in IoT: A Survey. **Wireless Personal Communications**, v. 115, n. 2, p. 1667–1693, 2020.

CHAOCHAISIT, W. et al. **Human Localization Sensor Ontology: Enabling OWL 2 DL-Based Search for User’s Location-Aware Sensors in the IoT**. IEEE Tenth International Conference on Semantic Computing (ICSC). **Anais**... Em: IEEE TENTH INTERNATIONAL CONFERENCE ON SEMANTIC COMPUTING (ICSC). Laguna Hills, CA, USA: 4 fev. 2016.

CHARMONMAN, S.; MONGKHONVANIT, P. **Special consideration for Big Data in IoE or Internet of Everything**. 13th International Conference on ICT and Knowledge Engineering (ICT & Knowledge Engineering 2015). **Anais**... Em: 13TH INTERNATIONAL CONFERENCE ON ICT AND KNOWLEDGE ENGINEERING (ICT & KNOWLEDGE ENGINEERING 2015). Bangkok, Thailand: IEEE, 18 nov.

2015. Disponível em: <http://ieeexplore.ieee.org/document/7368487/>. Acesso em: 31 maio. 2020

CHAVHAN, S.; KULKARNI, R. A.; ZILPE, A. R. Smart Sensors for IIoT in Autonomous Vehicles: Review. **Internet of Things**, p. 51–61, 2021.

CHELLAPPAN, V.; SIVALINGAM, K. M. Security and privacy in the Internet of Things. Em: **Internet of Things - Principles and Paradigms**. Burlington, MA, USA: Morgan Kaufmann, 2016. p. 183–200.

CHEN, C. et al. Deep Learning on Computational-Resource-Limited Platforms: A Survey. **Mobile Information Systems**, v. 2020, 2020.

CHEN, C.; HELAL, S. **A device-centric approach to a safer Internet of Things**. International Workshop on Networking and Object Memories for the Internet of Things. **Anais**...: NoME-IoT'11 - Proceedings of the 2011 International Workshop on Networking and Object Memories for the Internet of Things. Em: INTERNATIONAL WORKSHOP ON NETWORKING AND OBJECT MEMORIES FOR THE INTERNET OF THINGS. Beijing, China: 2011. Disponível em: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-80054051095&doi=10.1145%2f2029932.2029934&partnerID=40&md5=7256eab92afea71d60a9c3320d9e057b>

CHO, H. et al. **IoTIZER: A Versatile Mechanical Hijacking Device for Creating Internet of Old Things**. Designing Interactive Systems Conference 2021. **Anais**... Em: DIS '21: DESIGNING INTERACTIVE SYSTEMS CONFERENCE 2021. Virtual Event USA: ACM, 28 jun. 2021. Disponível em: <https://dl.acm.org/doi/10.1145/3461778.3461996>. Acesso em: 25 ago. 2021

COLLI, M. et al. A maturity assessment approach for conceiving context-specific roadmaps in the Industry 4.0 era. **Annual Reviews in Control**, v. 48, p. 165–177, 2019.

COMPTON, M. et al. The SSN ontology of the W3C semantic sensor network incubator group. **Web Semantics: Science, Services and Agents on the World Wide Web**, v. 17, p. 25–32, 1 dez. 2012.

CONSOLVO, S. et al. **Activity Sensing in the Wild: A Field Trial of Ubifit Garden**. Proceedings of the SIGCHI Conference on Human Factors in Computing Systems. **Anais**...: CHI '08.Florence, Italy: ACM, 5 abr. 2008. Disponível em: <http://doi.acm.org/10.1145/1357054.1357335>. Acesso em: 27 nov. 2019

COOK, C. et al. Score Reliability in Webor Internet-Based Surveys: Unnumbered Graphic Rating Scales versus Likert-Type Scales. **Educational and Psychological Measurement**, v. 61, n. 4, p. 697–706, Agosto 2001.

CORCHADO, J. M. et al. Deepint.net: A Rapid Deployment Platform for Smart Territories. **SENSORS**, v. 21, n. 1, jan. 2021.

COSTA, V. C. F. DA; OLIVEIRA, L. F.; SOUZA, J. DE. **A collaborative approach to support interoperability and awareness of Internet of Everything (IoE) enablers**. 2021 IEEE 2nd International Conference on Human-Machine Systems (ICHMS).

Anais... Em: 2021 IEEE 2ND INTERNATIONAL CONFERENCE ON HUMAN-MACHINE SYSTEMS (ICHMS). set. 2021.

COUTINHO, R. W. L.; BOUKERCHE, A. **Topology Control for Internet of Underwater Things**. Proceedings of the 15th ACM International Symposium on QoS and Security for Wireless and Mobile Networks - Q2SWinet'19. **Anais**... Em: THE 15TH ACM INTERNATIONAL SYMPOSIUM. Miami Beach, FL, USA: ACM Press, 2019. Disponível em: <http://dl.acm.org/citation.cfm?doid=3345837.3355962>. Acesso em: 25 ago. 2021

CUI, F. Deployment and integration of smart sensors with IoT devices detecting fire disasters in huge forest environment. **Computer Communications**, v. 150, p. 818–827, 2020.

DA COSTA, V. C. F.; OLIVEIRA, L.; DE SOUZA, J. **Towards A Taxonomy for Ranking Knowledge in Internet of Everything**. Proceedings of the 2021 IEEE 24th International Conference on Computer Supported Cooperative Work in Design, CSCWD 2021. **Anais**...2021. Disponível em: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85107725114&doi=10.1109%2fCSCWD49262.2021.9437857&partnerID=40&md5=914600bfd9bd9b5e3e35b0280d8db4ec>

DAMIANI, E. **Toward big data risk analysis**. IEEE International Conference on Big Data (Big Data). **Anais**... Em: IEEE INTERNATIONAL CONFERENCE ON BIG DATA (BIG DATA). Santa Clara, CA, USA: 29 nov. 2015.

DASU, S.; BRUNNER-SPERDIN, A. Designing Service Systems to Enhance Perceived Decision Control. Em: **Handbook of Service Science**. [s.l.] Springer International Publishing, 2019. v. II.

DATTA, P.; SHARMA, B. **A survey on IoT architectures, protocols, security and smart city based applications**. 8th International Conference on Computing, Communications and Networking Technologies, ICCCNT 2017. **Anais**...2017. Disponível em: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85041390292&doi=10.1109%2fICCCNT.2017.8203943&partnerID=40&md5=e415e54302d21b095a6644b5a6dae0b0>

DAVIES, M. Knowledge (Explicit, Implicit and Tacit): Philosophical Aspects. Em: **International Encyclopedia of the Social & Behavioral Sciences**. [s.l: s.n.]. p. 74–90.

DE AMORIM SILVA, R.; BRAGA, R. T. V. Enhancing Future Classroom Environments Based on Systems of Systems and the Internet of Anything. **IEEE Internet of Things Journal**, v. 7, n. 10, p. 10475–10482, out. 2020.

DE MATOS, E.; AMARAL, L. A.; HESSEL, F. Context-Aware Systems: Technologies and Challenges in Internet of Everything Environments. Em: BATALLA, J. M. et al. (Eds.). . **Beyond the Internet of Things**. Internet of Things. Cham, Germany: Springer International Publishing, 2017. p. 1–25.

DEFIEBRE, D.; SACHARIDIS, D.; GERMANAKOS, P. **A Decentralized Recommendation Engine in the Social Internet of Things**. Adjunct Publication of the 28th ACM Conference on User Modeling, Adaptation and Personalization. **Anais**...:

UMAP ’20 Adjunct.New York, NY, USA: Association for Computing Machinery, 14 jul. 2020. Disponível em: <http://doi.org/10.1145/3386392.3397602>. Acesso em: 25 ago. 2021

DI MARTINO, B. et al. **Internet of everything: Algorithms, Methodologies, Technologies and Perspectives**. New York, NY: Springer Singapore, 2018a.

DI MARTINO, B. et al. Trends and Strategic Researches in Internet of Everything. Em: DI MARTINO, B. et al. (Eds.). . **Internet of Everything**. Internet of Things. Singapore: Springer Singapore, 2018b. p. 1–12.

DIAMANTOULAKIS, P. D.; KARAGIANNIDIS, G. K. **Big data analytics for smart grids**. [s.l: s.n.].

DJENOURI, Y. et al. Sensor data fusion for the industrial artificial intelligence of things. **Expert Systems**, 2021.

DORSEMAINE, B. et al. **Internet of Things: A Definition & Taxonomy**. 9th International Conference on Next Generation Mobile Applications, Services and Technologies. **Anais**... Em: 9TH INTERNATIONAL CONFERENCE ON NEXT GENERATION MOBILE APPLICATIONS, SERVICES AND TECHNOLOGIES. Cambridge,UK: 9 set. 2015.

DRAGICEVIC, N. et al. **Modelling Knowledge Dynamics in Industry 4.0: A Smart Grid Scenario**. (Marimon, F and MasMachuca, M and BerbegalMirabent, J and Bastida, R, Ed.)PROCEEDINGS OF THE 18TH EUROPEAN CONFERENCE ON KNOWLEDGE MANAGEMENT (ECKM 2017), VOLS 1 AND 2. **Anais**...: Proceedings of the European Conference on Knowledge Management.2017.

DRESCH, A.; LACERDA, D. P.; ANTUNES, J. A. V. J. **Design Science Research: Método de Pesquisa para Avanço da Ciência e Tecnologia**. 1ª edição ed. [s.l.] Bookman, 2014.

DREYER, S. et al. Focusing the customer through smart services: a literature review. **Electronic Markets**, v. 29, n. 1, p. 55–78, mar. 2019.

EDWARDS, J. S. (ED.). **The Essentials of Knowledge Management**. London: Palgrave Macmillan UK, 2015.

EFFECTIVE | Meaning & Definition for UK English | Lexico.com. Disponível em: <https://www.lexico.com/definition/effective>. Acesso em: 2 mar. 2022.

EICHSTÄDT, S. et al. Toward smart traceability for digital sensors and the industrial internet of things. **Sensors**, v. 21, n. 6, p. 1–15, 2021.

EIN-DOR, P. Taxonomies of Knowledge. Em: **Encyclopedia of Knowledge Management, Second Edition**. 2. ed. Hershey, PA, USA: IGI Global, 2011. p. 1490–1499.

EL-SHEIKH, E.; ZIMMERMANN, A.; JAIN, L. C. (EDS.). **Emerging Trends in the Evolution of Service-Oriented and Enterprise Architectures**. Cham: Springer International Publishing, 2016. v. 111

ELSISI, M. et al. Reliable industry 4.0 based on machine learning and IOT for analyzing, monitoring, and securing smart meters. **Sensors (Switzerland)**, v. 21, n. 2, p. 1–16, 2021.

ERIS, O.; DRURY, J.; ERCOLINI, D. **A collaboration-focused taxonomy of the Internet of Things**. IEEE 2nd World Forum on Internet of Things (WF-IoT). **Anais**...: Different Perspectives on Classification of the Internet of Things. Em: IEEE 2ND WORLD FORUM ON INTERNET OF THINGS (WF-IOT). Milan, Italy: 14 dez. 2015.

ESTRIN, D. et al. Participatory sensing: applications and architecture [Internet Predictions]. **IEEE Internet Computing**, v. 14, n. 1, p. 12–42, jan. 2010.

ETZION, O.; FOURNIER, F.; ARCUSHIN, S. **Tutorial on the internet of everything**. Proceedings of the 8th ACM International Conference on Distributed Event-Based Systems - DEBS ’14. **Anais**... Em: THE 8TH ACM INTERNATIONAL CONFERENCE. Mumbai, India: ACM Press, 2014. Disponível em: <http://dl.acm.org/citation.cfm?doid=2611286.2611308>. Acesso em: 30 ago. 2018

EVANS, D. **The Internet of Everything: How More Relevant and Valuable Connections Will Change the World**. Point of View (Blog). Disponível em: <https://www.cisco.com/web/about/ac79/docs/innov/IoE.pdf.comiweb/aboutlac79/docs/innov/IoE.pdf>. Acesso em: 8 set. 2020.

FAN, H. et al. Capability representation model for heterogeneous remote sensing sensors: Case study on soil moisture monitoring. **Environmental Modelling & Software**, v. 70, p. 65–79, 1 ago. 2015.

FARAHZADI, A. et al. Middleware technologies for cloud of things-a survey. **Digital Communications and Networks**, 18 abr. 2017.

FARIAS DA COSTA, V. C.; OLIVEIRA, L.; DE SOUZA, J. Internet of Everything (IoE) Taxonomies: A Survey and a Novel Knowledge-Based Taxonomy. **Sensors**, v. 21, n. 2, p. 568, jan. 2021.

FARIAS, V.; OLIVEIRA, J.; SOUZA, J. Knowledge Management Integrating Organizational Learning in a Military Context: The 3M Model. **The International Journal of Knowledge, Culture, and Change Management: Annual Review**, v. 9, n. 1, p. 111–124, 2009.

FIAIDHI, J.; MOHAMMED, S. Internet of Everything as a Platform for Extreme Automation. **IT Professional**, v. 21, n. 1, p. 21–25, 2019.

FIORE, S. M. et al. Toward an Understanding of Macrocognition in Teams: Predicting Processes in Complex Collaborative Contexts. **Human Factors: The Journal of the Human Factors and Ergonomics Society**, v. 52, n. 2, p. 203–224, abr. 2010.

FIROUZI, F. et al. Internet-of-Things and big data for smarter healthcare: From device to architecture, applications and analytics. **Future Generation Computer Systems**, v. 78, p. 583–586, 2018.

FORTINO, G. et al. **On the Classification of Cyberphysical Smart Objects in the Internet of Things**. International Workshop on Networks of Cooperating Objects for

Smart Cities 2014 (UBICITEC 2014). **Anais**... Em: INTERNATIONAL WORKSHOP ON NETWORKS OF COOPERATING OBJECTS FOR SMART CITIES 2014 (UBICITEC 2014). Berlin, Germany: 2014.

FORTINO, G. et al. Towards Multi-layer Interoperability of Heterogeneous IoT Platforms: The INTER-IoT Approach. Em: GRAVINA, R. et al. (Eds.). . **Integration, Interconnection, and Interoperability of IoT Systems**. Internet of Things. Cham: Springer International Publishing, 2018. p. 199–232.

FOSTER, A.; FORD, N. Serendipity and information seeking: An empirical study. **Journal of Documentation**, v. 59, n. 3, p. 321–340, 2003.

FRANÇA, R. P. et al. The Fundamentals and Potential of the Internet of Vehicles (IoV) in Today's Society. **Internet of Things**, p. 3–29, 2021.

FRENCH, R.; BENAKIS, M.; MARIN-REYES, H. **Intelligent sensing for robotic re-manufacturing in aerospace - An industry 4.0 design based prototype**. Proceedings - 2017 IEEE 5th International Symposium on Robotics and Intelligent Sensors, IRIS 2017. **Anais**...2018. Disponível em: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85047417505&doi=10.1109%2fIRIS.2017.8250134&partnerID=40&md5=6f0d651dd26fc3c84fcd195b959deedd>

GADDAM, A. et al. Detecting sensor faults, anomalies and outliers in the internet of things: A survey on the challenges and solutions. **Electronics (Switzerland)**, v. 9, n. 3, 2020.

GANEK, A. Overview of Autonomic Computing: Origins, Evolution, Direction . . . . Alan Ganek. Em: **Autonomic Computing**. [s.l.] CRC Press, 2007.

GAO, J.; LEI, L.; YU, S. **Big Data Sensing and Service: A Tutorial**. IEEE First International Conference on Big Data Computing Service and Applications. **Anais**... Em: IEEE FIRST INTERNATIONAL CONFERENCE ON BIG DATA COMPUTING SERVICE AND APPLICATIONS. Redwood City, CA, USA: 30 abr. 2015.

GAO, T.; CHAI, Y.; LIU, Y. **A Review of Knowledge Management and Future Research Trend**. Proceedings of the 2nd International Conference on Crowd Science and Engineering. **Anais**...: ICCSE'17.New York, NY, USA: Association for Computing Machinery, 2017. Disponível em: <https://doi-org.ez29.periodicos.capes.gov.br/10.1145/3126973.3126997>

GAONKAR, S. et al. **Micro-Blog: sharing and querying content through mobile phones and social participation**. Proceeding of the 6th international conference on Mobile systems, applications, and services - MobiSys '08. **Anais**... Em: PROCEEDING OF THE 6TH INTERNATIONAL CONFERENCE ON MOBILE SYSTEMS, APPLICATIONS, AND SERVICES - MOBISYS '08. Breckenridge, CO, USA: ACM Press, 17 jun. 2008. Disponível em: <http://portal.acm.org/citation.cfm?doid=1378600.1378620>. Acesso em: 10 nov. 2020

GARCIA-MAGARINO, I.; LACUESTA, R.; LLORET, J. Agent-Based Simulation of Smart Beds with Internet-of-Things for Exploring Big Data Analytics. **IEEE Access**, v. 6, p. 366–379, 2017.

GATI, N. J. et al. Differentially Private Tensor Train Deep Computation for Internet of Multimedia Things. **ACM Transactions on Multimedia Computing, Communications, and Applications**, v. 16, n. 3s, p. 95:1-95:20, 31 dez. 2021.

GE, M.; BANGUI, H.; BUHNOVA, B. Big Data for Internet of Things: A Survey. **Future Generation Computer Systems**, v. 87, p. 601–614, out. 2018.

GENNARI, R.; MELONIO, A. **Designing the internet of tangible things for outdoors environments with university students**. Proceedings of the 13th Biannual Conference of the Italian SIGCHI Chapter on Designing the next interaction - CHItaly '19. **Anais**... Em: THE 13TH BIANNUAL CONFERENCE OF THE ITALIAN SIGCHI CHAPTER. Padova, Italy: ACM Press, 2019. Disponível em: <http://dl.acm.org/citation.cfm?doid=3351995.3352046>. Acesso em: 25 ago. 2021

GHOSH, A.; CHAKRABORTY, D.; LAW, A. Artificial intelligence in Internet of things. **CAAI Transactions on Intelligence Technology**, v. 3, n. 4, p. 208–218, 1 dez. 2018.

GIL, D. et al. Internet of Things: A Review of Surveys Based on Context Aware Intelligent Services. **Sensors**, v. 16, n. 7, p. 1069, 11 jul. 2016.

GLUHAK, A. et al. A survey on facilities for experimental internet of things research. **IEEE Communications Magazine**, v. 49, n. 11, p. 58–67, nov. 2011.

GOBBLE, M. M. Digitalization, Digitization, and Innovation. **Research-Technology Management**, v. 61, n. 4, p. 56–59, 4 jul. 2018.

GOMBA, M.; NLEYA, B. **Overview Access and Control Considerations for Internet of Things**. 2018 International Conference on Advances in Big Data, Computing and Data Communication Systems, icABCD 2018. **Anais**...2018. Disponível em: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85054645789&doi=10.1109%2fICABCD.2018.8465435&partnerID=40&md5=b923884441e038bbea2c12cc44b49b89>

GOMES, J. B. A. et al. IoT-enabled gas sensors: Technologies, applications, and opportunities. **Journal of Sensor and Actuator Networks**, v. 8, n. 4, 2019.

GRANT, J.; PARISI, F. Logic and Knowledge Bases. Em: **Encyclopedia of Knowledge Management, Second Edition**. 2. ed. Hershey, PA, USA,: David Schwartz (Bar-Ilan University, Israel) and Dov Te'eni (Tel-Aviv University , Israel), 2010.

GRECO, L.; RITROVATO, P.; XHAFA, F. An edge-stream computing infrastructure for real-time analysis of wearable sensors data. **Future Generation Computer Systems**, v. 93, p. 515–528, 2019.

GUPTA, V. P. Smart Sensors and Industrial IoT (IIoT): A Driver of the Growth of Industry 4.0. **Internet of Things**, p. 37–49, 2021.

GUTWIN, C.; GREENBERG, S. The importance of awareness for team cognition in distributed collaboration. Em: SALAS, E.; FIORE, S. M. (Eds.). . **Team cognition: Understanding the factors that drive process and performance.** Washington,DC, USA: American Psychological Association, 2004. p. 177–201.

HALDORAI, A.; RAMU, A.; SURIYA, M. Organization Internet of Things (IoTs): Supervised, Unsupervised, and Reinforcement Learning. **EAI/Springer Innovations in Communication and Computing**, p. 27–53, 2020.

HALLER, S. et al. **A Domain Model for the Internet of Things**. IEEE International Conference on Green Computing and Communications and IEEE Internet of Things and IEEE Cyber, Physical and Social Computing. **Anais**... Em: IEEE INTERNATIONAL CONFERENCE ON GREEN COMPUTING AND COMMUNICATIONS AND IEEE INTERNET OF THINGS AND IEEE CYBER, PHYSICAL AND SOCIAL COMPUTING. Beijing, China: 20 ago. 2013.

HAMAD, S. A. et al. **IoT device identification via network-flow based fingerprinting and learning**. Proceedings - 2019 18th IEEE International Conference on Trust, Security and Privacy in Computing and Communications/13th IEEE International Conference on Big Data Science and Engineering, TrustCom/BigDataSE 2019. **Anais**...2019. Disponível em: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85075160731&doi=10.1109%2fTrustCom%2fBigDataSE.2019.00023&partnerID=40&md5=1c606725857fa209f98efe1f0403d28b>

HAMILTON, M. et al. Transafe. **SIGCAS Comput. Soc**, p. 32–37, dez. 2011.

HAMMOUDI, S.; ALIOUAT, Z.; HAROUS, S. **A new Infrastructure as a Service for IoT-Cloud**. 2018 14th International Wireless Communications and Mobile Computing Conference, IWCMC 2018. **Anais**...2018. Disponível em: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85053914518&doi=10.1109%2fIWCMC.2018.8450503&partnerID=40&md5=bbb11910095de8a199931250b30cd8ab>

HARON, N. et al. **Data trustworthiness in Internet of Things: A taxonomy and future directions**. IEEE Conference on Big Data and Analytics (ICBDA). **Anais**... Em: IEEE CONFERENCE ON BIG DATA AND ANALYTICS (ICBDA). Kuching, Malaysia: 16 nov. 2017.

HASSAN, N. et al. The Role of Edge Computing in Internet of Things. **IEEE Communications Magazine**, v. 56, n. 11, p. 110–115, nov. 2018.

HAURI, Y. et al. **"Internet from Space" without Inter-satellite Links**. Proceedings of the 19th ACM Workshop on Hot Topics in Networks. **Anais**... Em: HOTNETS '20: THE 19TH ACM WORKSHOP ON HOT TOPICS IN NETWORKS. Virtual Event USA: ACM, 4 nov. 2020. Disponível em: <https://dl.acm.org/doi/10.1145/3422604.3425938>. Acesso em: 25 ago. 2021

HEVNER, A. R. et al. Design Science in Information Systems Research. **MIS Q.**, v. 28, n. 1, p. 75–105, mar. 2004.

HÖLLER, J.; TSIATSIS, V.; MULLIGAN, C. Toward a Machine Intelligence Layer for Diverse Industrial IoT Use Cases. **IEEE Intelligent Systems**, v. 32, n. 4, p. 64–71, 2017.

HONTI, G. M.; ABONYI, J. A Review of Semantic Sensor Technologies in Internet of Things Architectures. **Complexity**, v. 2019, 2019.

HUANG, S. et al. **Internet of Service: the Business Operating Environment of Crowd System**. Proceedings of the 4th International Conference on Crowd Science and Engineering. **Anais**... Em: ICCSE'19: THE 4TH INTERNATIONAL CONFERENCE ON CROWD SCIENCE AND ENGINEERING. Jinan China: ACM, 18 out. 2019. Disponível em: <https://dl.acm.org/doi/10.1145/3371238.3371262>. Acesso em: 25 ago. 2021

HUANG, Y.; ZHANG, P.; JIN, Z. **Improving business operation efficiency by using Smart Contract**. ACM International Conference Proceeding Series. **Anais**...2021. Disponível em: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85109566144&doi=10.1145%2f3456126.3456131&partnerID=40&md5=bac2162d4b96c324ec71e707ac6d4090>

HUI, T. K. L.; SHERRATT, R. S. Towards disappearing user interfaces for ubiquitous computing: human enhancement from sixth sense to super senses. **Journal of Ambient Intelligence and Humanized Computing**, v. 8, n. 3, p. 449–465, 1 jun. 2017.

HUNG, Y.-H.; WU, S.-H. **Investigating the Effect of the Cloud Computing on Education Internet of Things (Eiot)**. Proceedings of the 2nd International Conference on Computing and Big Data - ICCBD 2019. **Anais**... Em: THE 2ND INTERNATIONAL CONFERENCE. Taichung, Taiwan: ACM Press, 2019. Disponível em: <http://dl.acm.org/citation.cfm?doid=3366650.3366674>. Acesso em: 25 ago. 2021

IQBAL, K. et al. Intelligent transportation system (ITS) for smart-cities using Mamdani Fuzzy Inference System. **International Journal of Advanced Computer Science and Applications**, v. 9, n. 2, p. 94–105, 2018.

IRSHAD, M. **A Systematic Review of Information Security Frameworks in the Internet of Things (IoT)**. 2016 IEEE 18th International Conference on High Performance Computing and Communications; IEEE 14th International Conference on Smart City; IEEE 2nd International Conference on Data Science and Systems (HPCC/SmartCity/DSS). **Anais**... Em: 2016 IEEE 18TH INTERNATIONAL CONFERENCE ON HIGH PERFORMANCE COMPUTING AND COMMUNICATIONS; IEEE 14TH INTERNATIONAL CONFERENCE ON SMART CITY; IEEE 2ND INTERNATIONAL CONFERENCE ON DATA SCIENCE AND SYSTEMS (HPCC/SMARTCITY/DSS). dez. 2016.

JACOB, S. et al. AI and IoT-Enabled smart exoskeleton system for rehabilitation of paralyzed people in connected communities. **IEEE Access**, v. 9, p. 80340–80350, 2021.

JANEERA, D. A. et al. Internet of Things and Artificial Intelligence-Enabled Secure Autonomous Vehicles for Smart Cities. **EAI/Springer Innovations in Communication and Computing**, p. 201–218, 2021.

JENNEX, M. E. Big Data, the Internet of Things, and the Revised Knowledge Pyramid. **SIGMIS Database**, v. 48, n. 4, p. 69–79, nov. 2017a.

JENNEX, M. E. Big Data, the Internet of Things, and the Revised Knowledge Pyramid. **SIGMIS Database**, v. 48, n. 4, p. 69–79, nov. 2017b.

JESSE, N. Internet of Things and Big Data: the disruption of the value chain and the rise of new software ecosystems. **AI and Society**, v. 33, n. 2, p. 229–239, 2018.

JIENAN, D.; XIANGNING, C.; SHUAI, C. **Overview of Application Layer Protocol of Internet of Things**. 2021 IEEE 6th International Conference on Computer and Communication Systems, ICCCS 2021. **Anais**...2021. Disponível em: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85113314276&doi=10.1109%2fICCCS52626.2021.9449252&partnerID=40&md5=92b131ff05ddd0651741a929ceb29a41>

JING, Q. et al. Security of the Internet of Things: perspectives and challenges. **Wireless Networks**, v. 20, n. 8, p. 2481–2501, 1 nov. 2014.

JUNIOR, R. L. **IoT applications for monitoring companion animals: A systematic literature review**. Proceedings of the 2020 14th International Conference on Innovations in Information Technology, IIT 2020. **Anais**...2020. Disponível em: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85099435484&doi=10.1109%2fIIT50501.2020.9299045&partnerID=40&md5=5ad1d5b9d0890334747294a4f9d8fdd8>

KAMIENSKI, C. A. et al. Context Design and Tracking for IoT-Based Energy Management in Smart Cities. **IEEE Internet of Things Journal**, v. 5, n. 2, p. 687–695, 2018.

KAMTHAN, P.; FANCOTT, T. A Knowledge Management Model for Patterns. Em: **Knowledge Management Encyclopedia**. [s.l.] IGI Global, 2011. v. 2.

KANG, B. et al. DETN: Delay-Efficient Tolerant Network for Internet of Planet. **IEEE Sensors Journal**, v. 21, n. 2, p. 2377–2384, jan. 2021.

KANG, B.; KIM, D.; CHOO, H. Internet of Everything: A Large-Scale Autonomic IoT Gateway. **IEEE Transactions on Multi-Scale Computing Systems**, v. 3, n. 3, p. 206–214, jul. 2017.

KANJO, E. et al. MobSens: Making Smart Phones Smarter. **IEEE Pervasive Computing**, v. 8, n. 4, p. 50–57, out. 2009.

KARABEGOVIĆ, I. et al. Implementation of Industry 4.0 and Industrial Robots in the Manufacturing Processes. **Lecture Notes in Networks and Systems**, v. 76, p. 3–14, 2020.

KAUR, K. et al. Container-as-a-Service at the Edge: Trade-off between Energy Efficiency and Service Availability at Fog Nano Data Centers. **IEEE Wireless Communications**, v. 24, n. 3, p. 48–56, 2017.

KEPHART, J. O.; CHESS, D. M. The vision of autonomic computing. **Computer**, v. 36, n. 1, p. 41–50, jan. 2003.

KHAN, W. Z. et al. When social objects collaborate: Concepts, processing elements, attacks and challenges. **Computers & Electrical Engineering**, v. 58, p. 397–411, fev. 2017.

KHAN, Z.; VORLEY, T. Big data text analytics: an enabler of knowledge management. **Journal of Knowledge Management**, v. 21, n. 1, p. 18–34, 13 fev. 2017.

KHODADADI, F.; DASTJERDI, A. V.; BUYYA, R. Chapter 1 - Internet of Things: an overview. Em: **Internet of Things**. [s.l.] Morgan Kaufmann, 2016. p. 3–27.

KHRAIS, L. T. **The Combination of IoT-Sensors in Appliances and block-chain Technology in Smart Cities Energy Solutions**. 2020 6th International Conference on Advanced Computing and Communication Systems, ICACCS 2020. **Anais**...2020. Disponível em: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85084656069&doi=10.1109%2fICACCS48705.2020.9074362&partnerID=40&md5=962d5253873d3bbdd9e74fac4c3e72c0>

KIM, H. Service Science: Past, Present, and Future. **Journal of Service Science Research**, v. 11, n. 2, p. 117–132, dez. 2019.

KITCHENHAM, B. et al. Systematic literature reviews in software engineering – A tertiary study. **Information and Software Technology**, v. 52, n. 8, p. 792–805, ago. 2010.

KOCAKULAK, M.; BUTUN, I. **An overview of Wireless Sensor Networks towards internet of things**. 2017 IEEE 7th Annual Computing and Communication Workshop and Conference, CCWC 2017. **Anais**...2017. Disponível em: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85016770978&doi=10.1109%2fCCWC.2017.7868374&partnerID=40&md5=7459e9760dfe2cd7d5dabe11ef6ff0a1>

KOEHLER, J. et al. On Autonomic Computing Architectures. p. 11, 2003.

KOLAR, P.; BENAVIDEZ, P.; JAMSHIDI, M. Survey of Datafusion Techniques for Laser and Vision Based Sensor Integration for Autonomous Navigation. **Sensors**, v. 20, n. 8, p. 2180, 12 abr. 2020.

KOMPELLA, L. Socio-Technical Transitions and Organizational Responses: Insights from E-Governance Case Studies. **JOURNAL OF GLOBAL INFORMATION TECHNOLOGY MANAGEMENT**, v. 23, n. 2, p. 89–111, 2 abr. 2020.

KORONIOTIS, N. et al. A Holistic Review of Cybersecurity and Reliability Perspectives in Smart Airports. **IEEE Access**, v. 8, p. 209802–209834, 2020.

KOTIS, K. I.; VOUROS, G. A.; SPILIOTOPOULOS, D. Ontology engineering methodologies for the evolution of living and reused ontologies: status, trends, findings and recommendations. **The Knowledge Engineering Review**, v. 35, ed 2020.

KOTIS, K.; KATASONOV, A. Semantic Interoperability on the Internet of Things: The Semantic Smart Gateway Framework. **International Journal of Distributed Systems and Technologies**, v. 4, n. 3, p. 47–69, jul. 2013.

KULKARNI, S.; VANI, R. M.; HUNAGUND, P. V. Review on IoT Based Case Study: Applications and Challenges. **Lecture Notes on Data Engineering and Communications Technologies**, v. 26, p. 1487–1494, 2019.

KUMAR, P.; TRIPATHI, R.; P. GUPTA, G. **P2IDF: A Privacy-Preserving based Intrusion Detection Framework for Software Defined Internet of Things-Fog (SDIoT-Fog)**. Adjunct Proceedings of the 2021 International Conference on Distributed Computing and Networking. **Anais**... Em: ICDCN ’21: INTERNATIONAL CONFERENCE ON DISTRIBUTED COMPUTING AND NETWORKING 2021. Nara Japan: ACM, 5 jan. 2021. Disponível em: <https://dl.acm.org/doi/10.1145/3427477.3429989>. Acesso em: 25 ago. 2021

KURNIABUDI et al. **Preprocessing and Framework for Unsupervised Anomaly Detection in IoT: Work on Progress**. 2018 International Conference on Electrical Engineering and Computer Science (ICECOS). **Anais**... Em: 2018 INTERNATIONAL CONFERENCE ON ELECTRICAL ENGINEERING AND COMPUTER SCIENCE (ICECOS). Pangkal Pinang: IEEE, out. 2018. Disponível em: <https://ieeexplore.ieee.org/document/8605231/>. Acesso em: 25 out. 2019

LALANDA, P.; MCCANN, J. A.; DIACONESCU, A. Future of Autonomic Computing and Conclusions. Em: LALANDA, P.; MCCANN, J. A.; DIACONESCU, A. (Eds.). . **Autonomic Computing: Principles, Design and Implementation**. Undergraduate Topics in Computer Science. London: Springer, 2013. p. 263–278.

LAMMEL, G. et al. **Smart System Architecture for Sensors with Integrated Signal Processing and AI**. 2021 Smart Systems Integration (SSI). **Anais**... Em: 2021 SMART SYSTEMS INTEGRATION (SSI). abr. 2021.

LANGLEY, D. J. et al. The Internet of Everything: Smart things and their impact on business models. **Journal of Business Research**, v. 122, p. 853–863, jan. 2020.

LE-PHUOC, D.; HAUSWIRTH, M. Linked Data for Internet of Everything. Em: GRAVINA, R. et al. (Eds.). . **Integration, Interconnection, and Interoperability of IoT Systems**. Internet of Things. Cham: Springer International Publishing, 2018. p. 129–148.

LIM, C.; MAGLIO, P. P. Clarifying the Concept of Smart Service System. Em: **Handbook of Service Science**. [s.l.] Springer International Publishing, 2019. v. II.

LIPPI, M. et al. An argumentation-based perspective over the social IoT. **IEEE Internet of Things Journal**, v. 5, n. 4, p. 2537–2547, 2018.

LOHIYA, R.; THAKKAR, A. Application Domains, Evaluation Data Sets, and Research Challenges of IoT: A Systematic Review. **IEEE Internet of Things Journal**, v. 8, n. 11, p. 8774–8798, jun. 2021.

LV, Z.; QIAO, L.; SONG, H. Analysis of the Security of Internet of Multimedia Things. **ACM Transactions on Multimedia Computing, Communications, and Applications**, v. 16, n. 3s, p. 97:1-97:16, 16 dez. 2020.

MA, L.; SUN, N.; SONG, X. **Research on Knowledge Service Models in Digital Library**. 2015 7th International Conference on Information Technology in Medicine and Education (ITME). **Anais**... Em: 2015 7TH INTERNATIONAL CONFERENCE ON INFORMATION TECHNOLOGY IN MEDICINE AND EDUCATION (ITME). Huangshan, China: IEEE, nov. 2015. Disponível em: <http://ieeexplore.ieee.org/document/7429211/>. Acesso em: 3 mar. 2021

MAGLIO, P. P. et al. (EDS.). **Handbook of Service Science, Volume II**. Cham: Springer International Publishing, 2019.

MAHAKALKAR, N. et al. **Smart interface development for sensor data analytics in internet of robotic things**. 2019 International Conference on Intelligent Computing and Control Systems, ICCS 2019. **Anais**...2019. Disponível em: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85084077628&doi=10.1109%2fICCS45141.2019.9065531&partnerID=40&md5=d1934b87e48a15ec08fc11260cdc493d>

MAHDAVINEJAD, M.; REZVAN, M.; BAREKATAIN, M. Machine learning for internet of things data analysis: a survey. **Digital Communications and Networks**, v. 4, n. 3, p. 161–175, 1 ago. 2018.

MAISONNEUVE, N. et al. **NoiseTube: Measuring and mapping noise pollution with mobile phones**. (I. N. Athanasiadis et al., Eds.)Information Technologies in Environmental Engineering. **Anais**...: Environmental Science and Engineering.Berlin, Heidelberg: Springer, 2009.

MAITI, P. et al. **Efficient Data Collection for IoT Services in Edge Computing Environment**. Proceedings - 2017 International Conference on Information Technology, ICIT 2017. **Anais**...2018. Disponível em: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85051578432&doi=10.1109%2fICIT.2017.40&partnerID=40&md5=120a79424052d751fa3095be16826c4f>

MAJEED, A. **Developing countries and Internet-of-Everything (IoE)**. 2017 IEEE 7th Annual Computing and Communication Workshop and Conference (CCWC). **Anais**... Em: 2017 IEEE 7TH ANNUAL COMPUTING AND COMMUNICATION WORKSHOP AND CONFERENCE (CCWC). jan. 2017.

MAKRI, S. et al. “Making my own luck”: Serendipity strategies and how to support them in digital information environments. **Journal of the Association for Information Science and Technology**, v. 65, n. 11, p. 2179–2194, 2014.

MALDONADO, F. J. et al. **Smart Transducer Integrator (STI) for standardized system-of-systems monitoring**. 2018 IEEE International Instrumentation and Measurement Technology Conference (I2MTC). **Anais**... Em: 2018 IEEE INTERNATIONAL INSTRUMENTATION AND MEASUREMENT TECHNOLOGY

CONFERENCE (I2MTC). Houston, TX: IEEE, maio 2018. Disponível em: <https://ieeexplore.ieee.org/document/8409777/>. Acesso em: 25 out. 2019

MALÍK, P.; KRIŠTOFÍK, Š. Ai architectures for very smart sensors. **Internet of Things**, p. 391–439, 2020.

MANOGARAN, G. et al. Smart Sensing Based Functional Control for Reducing Uncertainties in Agricultural Farm Data Analysis. **IEEE Sensors Journal**, v. 21, n. 16, p. 17469–17478, ago. 2021.

MARJANI, M. et al. Big IoT Data Analytics: Architecture, Opportunities, and Open Research Challenges. **IEEE Access**, v. 5, p. 5247–5261, 2017.

MARKIEWICZ, M. et al. Predictive maintenance of induction motors using ultra-low power wireless sensors and compressed recurrent neural networks. **IEEE Access**, v. 7, p. 178891–178902, 2019.

MASOUD, M. et al. Sensors of Smart Devices in the Internet of Everything (IoE) Era: Big Opportunities and Massive Doubts. **Journal of Sensors**, v. 2019, p. 1–26, 2019.

MASTERS, K. L. et al. Galaxy Zoo: Bars in Disk Galaxies. **Monthly Notices of the Royal Astronomical Society**, v. 411, n. 3, p. 2026–2034, 1 mar. 2011.

MCCAY-PEET, L.; TOMS, E. G. Researching serendipity in digital information environments. **Synthesis Lectures on Information Concepts, Retrieval, and Services**, v. 9, n. 6, p. 1–109, 2018.

MCCAY-PEET, L.; TOMS, E. G.; KELLOWAY, E. K. Examination of relationships among serendipity, the environment, and individual differences. **Information Processing & Management**, v. 51, n. 4, p. 391–412, 1 jul. 2015.

MCLAMORE, E. S. et al. SNAPS: Sensor Analytics Point Solutions for Detection and Decision Support Systems. **Sensors**, v. 19, n. 22, p. 4935, 13 nov. 2019.

MCTIC. **Brazil in the digital transformation: Opportunities and challenges | Going Digital in Brazil | OECD iLibrary**. Disponível em: <https://www.oecd-ilibrary.org/sites/c5840db0-en/index.html?itemId=/content/component/c5840db0-en#sec-16>. Acesso em: 21 abr. 2021.

MEERADEVI; MUNDADA, M. R.; SANJAYKUMAR, J. H. **Review on Rapid Application Development using IoT**. International Conference on Current Trends in Computer, Electrical, Electronics and Communication, CTCEEC 2017. **Anais**...2018. Disponível em: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85054085427&doi=10.1109%2fCTCEEC.2017.8455108&partnerID=40&md5=849e746fb1e150edda1374530aacdcbf>

MEHMOOD, Y. et al. Internet-of-Things-Based Smart Cities: Recent Advances and Challenges. **IEEE Communications Magazine**, v. 55, n. 9, p. 16–24, 2017.

MELO, G. et al. **Towards an observatory for mobile participatory sensing applications**. IEEE 21st International Conference on Computer Supported Cooperative Work in Design (CSCWD). **Anais**... Em: IEEE 21ST INTERNATIONAL

CONFERENCE ON COMPUTER SUPPORTED COOPERATIVE WORK IN DESIGN (CSCWD). Wellington, New Zealand: IEEE, 26 abr. 2017. Disponível em: <http://ieeexplore.ieee.org/document/8066712/>. Acesso em: 19 mar. 2019

METALLIDOU, C. K.; PSANNIS, K. E.; EGYPTIADOU, E. A. Energy Efficiency in Smart Buildings: IoT Approaches. **IEEE Access**, v. 8, p. 63679–63699, 2020.

MILUZZO, E. et al. **Sensing Meets Mobile Social Networks: The Design, Implementation and Evaluation of the CenceMe Application**. Proceedings of the 6th ACM Conference on Embedded Network Sensor Systems. **Anais**...: SenSys ’08. Em: PROCEEDINGS OF THE 6TH ACM CONFERENCE ON EMBEDDED NETWORK SENSOR SYSTEMS. New York, NY, USA: ACM, 5 nov. 2008. Disponível em: <http://doi.acm.org/10.1145/1460412.1460445>. Acesso em: 27 nov. 2019

MIRAZ, M. H. et al. **A review on Internet of Things (IoT), Internet of Everything (IoE) and Internet of Nano Things (IoNT)**. 2015 Internet Technologies and Applications (ITA). **Anais**... Em: 2015 INTERNET TECHNOLOGIES AND APPLICATIONS (ITA). set. 2015.

MIRAZ, M. H. et al. **Internet of Nano-Things, Things and Everything: Future Growth TrendsFuture Internet**ST ALBAN-ANLAGE 66, CH-4052 BASEL, SWITZERLANDMDPI, , 2018.

MIRAZ, M. H.; ALI, M.; EXCELL, P. S. A Review on Internet ofThings (loT), Internet of Everything (IoE) and Internet ofNano Things (IoNT). **Internet Technologies and Applications (ITA)**, Internet Technologies and Applications (ITA). p. 219–224, 8 set. 2015.

MOHAMED, A. et al. The state of the art and taxonomy of big data analytics: view from new big data framework. **Artificial Intelligence Review**, 1 fev. 2019.

MON, A. et al. **Evaluation of technological development for the definition of Industries 4.0**. Congreso Argentino de Ciencias de la Informática y Desarrollos de Investigación (CACIDI). **Anais**... Em: CONGRESO ARGENTINO DE CIENCIAS DE LA INFORMÁTICA Y DESARROLLOS DE INVESTIGACIÓN (CACIDI). Buenos Aires, Argentina: 28 nov. 2018.

MONTEIRO JR, P. C. et al. **ABPM: Autonomic Business Process Manager**. LAACS 2008. **Anais**... Em: LAACS 2008. GRamado: 2008.

MONTORI, F. et al. The Curse of Sensing: Survey of techniques and challenges to cope with sparse and dense data in mobile crowd sensing for Internet of Things. **Pervasive and Mobile Computing**, v. 49, p. 111–125, 1 set. 2018.

MORELLI, N.; DE GÖTZEN, A.; SIMEONE, L. **Service Design Capabilities**. Cham: Springer International Publishing, 2021. v. 10

MOSCOSO-ZEA, O. et al. A Hybrid Infrastructure of Enterprise Architecture and Business Intelligence Analytics for Knowledge Management in Education. **IEEE Access**, v. 7, p. 38778–38788, 2019.

MOUNTROUIDOU, X.; BILLINGS, B.; MEJIA-RICART, L. Not just another Internet of Things taxonomy: A method for validation of taxonomies. **Internet of Things**, v. 6, p. 100049, 1 jun. 2019.

MOURTZIS, D.; MILAS, N.; VLACHOU, A. An internet of things-based monitoring system for shop-floor control. **Journal of Computing and Information Science in Engineering**, v. 18, n. 2, 2018.

MOUSTAKA, V.; VAKALI, A.; ANTHOPOULOS, L. G. A Systematic Review for Smart City Data Analytics. **ACM Computing Surveys**, v. 51, n. 5, p. 1–41, 4 dez. 2018.

NACHMAN, L. et al. **Jog Falls: A Pervasive Healthcare Platform for Diabetes Management**. (P. Floréen, A. Krüger, M. Spasojevic, Eds.)Pervasive Computing. **Anais**...: Lecture Notes in Computer Science. Em: PERVASIVE COMPUTING. Berlin, Heidelberg: Springer, 2010.

NAHA, R. K. et al. Fog Computing: Survey of Trends, Architectures, Requirements, and Research Directions. **IEEE Access**, v. 6, p. 47980–48009, 2018.

NAYYER, M. Z.; RAZA, I.; HUSSAIN, S. A. A Survey of Cloudlet-Based Mobile Augmentation Approaches for Resource Optimization. **ACM Computing Surveys (CSUR)**, v. 51, n. 5, p. 107, 23 jan. 2019.

NESHENKO, N. et al. Demystifying IoT Security: An Exhaustive Survey on IoT Vulnerabilities and a First Empirical Look on Internet-Scale IoT Exploitations. **IEEE Communications Surveys & Tutorials**, v. 21, n. 3, p. 2702–2733, 2019.

NETO, R. **Balanced Scorecard Autonômico: Um Arcabouço de Referência**. [s.l.] PESC UFRJ, 2012.

NEZAMI, Z.; ZAMANIFAR, K. Internet of Things/Internet of Everything: Structure and Ingredients. **IEEE Potentials**, v. 38, n. 2, p. 12–17, mar. 2019.

NICKERSON, R. C.; VARSHNEY, U.; MUNTERMANN, J. A method for taxonomy development and its application in information systems. **European Journal of Information Systems**, v. 22, n. 3, p. 336–359, maio 2013.

NIKIFOROVA, A. Smarter Open Government Data for Society 5.0: Are Your Open Data Smart Enough? **Sensors**, v. 21, n. 15, p. 5204, 31 jul. 2021.

NING, H. et al. From IoT to Future Cyber-Enabled Internet of X and Its Fundamental Issues. **IEEE Internet of Things Journal**, v. 8, n. 7, p. 6077–6088, abr. 2021.

NONAKA, I.; KONNO, N. The Concept of “Ba”: Building a Foundation for Knowledge Creation. **California Management Review**, v. 40, n. 3, p. 40–54, abr. 1998.

NONAKA, I.; TOYAMA, R. The Knowledge-creating Theory Revisited: Knowledge Creation as a Synthesizing Process. Em: **The Essentials of Knowledge Management**. London, UK: Palgrave Macmillan, 2015. p. 95–110.

NOURA, M.; ATIQUZZAMAN, M.; GAEDKE, M. Interoperability in Internet of Things: Taxonomies and Open Challenges. **Mobile Networks and Applications**, v. 24, n. 3, p. 796–809, jun. 2019.

OBERLÄNDER, A. M. et al. Conceptualizing business-to-thing interactions – A sociomaterial perspective on the Internet of Things. **European Journal of Information Systems**, v. 27, n. 4, p. 486–502, 4 jul. 2018.

OBINIKPO, A. A.; KANTARCI, B. Big Sensed Data Meets Deep Learning for Smarter Health Care in Smart Cities. **Journal of Sensor and Actuator Networks**, v. 6, n. 4, p. 26, dez. 2017.

OCED. **SERENDIPITY | Definition of SERENDIPITY by Oxford Dictionary on Lexico.com also meaning of SERENDIPITY**. Disponível em: <https://www.lexico.com/definition/serendipity>. Acesso em: 6 jul. 2021.

OCHS, T.; RIEMANN, U. **Knowledge management as a service: When big data meets knowledge management**. IoTBD 2016 - Proceedings of the International Conference on Internet of Things and Big Data. **Anais**...2016. Disponível em: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-84979498043&doi=10.5220%2f0005851703150323&partnerID=40&md5=b7e300f1cc5ee983561a559b17d359a3>

OSIFEKO, M. O.; HANCKE, G. P.; ABU-MAHFOUZ, A. M. Artificial intelligence techniques for cognitive sensing in future IoT: State-of-the-Art, potentials, and challenges. **Journal of Sensor and Actuator Networks**, v. 9, n. 2, 2020.

OTEAFY, S. M. A.; HASSANEIN, H. S. Leveraging Tactile Internet Cognizance and Operation via IoT and Edge Technologies. **Proceedings of the IEEE**, v. 107, n. 2, p. 364–375, fev. 2019.

OURIQUES, L. et al. **Analyzing Knowledge Codification for Planning Military Operations**. 2019 IEEE International Conference on Systems, Man and Cybernetics (SMC). **Anais**... Em: 2019 IEEE INTERNATIONAL CONFERENCE ON SYSTEMS, MAN AND CYBERNETICS (SMC). out. 2019.

PACHAYAPPAN, M.; GANESHKUMAR, C.; SUGUNDAN, N. **Technological implication and its impact in agricultural sector: An IoT Based Collaboration framework**. Procedia Computer Science. **Anais**...2020. Disponível em: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85086629401&doi=10.1016%2fj.procs.2020.04.125&partnerID=40&md5=3ac6662d84324f64b4b4df4b767ea97e>

PAL, D.; VANIJJA, V.; VARADARAJAN, V. **Quality Provisioning in the Internet of Things Era: Current State and Future Directions**. Proceedings of the 10th International Conference on Advances in Information Technology. **Anais**... Em: PROCEEDINGS OF THE 10TH INTERNATIONAL CONFERENCE ON ADVANCES IN INFORMATION TECHNOLOGY. Bangkok, Thailand: ACM, 10 dez. 2018. Disponível em: <http://dl-acm-org.ez29.capes.proxy.ufrj.br/citation.cfm?id=3291280.3291790>. Acesso em: 23 jul. 2019

PAL, S. et al. Security requirements for the internet of things: A systematic approach. **Sensors (Switzerland)**, v. 20, n. 20, p. 1–34, 2020.

PARK, S.-M.; KIM, Y.-G. A Metaverse: Taxonomy, Components, Applications, and Open Challenges. **IEEE Access**, v. 10, p. 4209–4251, 2022.

PASCHEN, J.; KIETZMANN, J.; KIETZMANN, T. C. Artificial intelligence (AI) and its implications for market knowledge in B2B marketing. **Journal of Business & Industrial Marketing**, v. 34, n. 7, p. 1410–1419, 5 ago. 2019.

PATCHAVA, V.; KANDALA, H. B.; BABU, P. R. **A Smart Home Automation technique with Raspberry Pi using IoT**. 2015 International Conference on Smart Sensors and Systems, IC-SSS 2015. **Anais**...2017. Disponível em: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85017214319&doi=10.1109%2fSMARTSENS.2015.7873584&partnerID=40&md5=8d035f830148b0884123d7b548277b8e>

PAUKSTADT, U.; STROBEL, G.; EICKER, S. UNDERSTANDING SERVICES IN THE ERA OF THE INTERNET OF THINGS: A SMART SERVICE TAXONOMY. **Proceedings of the 27th European Conference on Information Systems (ECIS)**, p. 19, 2019.

PEFFERS, K. et al. A Design Science Research Methodology for Information Systems Research. **J. Manage. Inf. Syst.**, v. 24, n. 3, p. 45–77, dez. 2007.

PENNEKAMP, J. et al. **Dataflow Challenges in an Internet of Production: A Security & Privacy Perspective**. Proceedings of the ACM Workshop on Cyber-Physical Systems Security & Privacy - CPS-SPC'19. **Anais**... Em: THE ACM WORKSHOP. London, United Kingdom: ACM Press, 2019. Disponível em: <http://dl.acm.org/citation.cfm?doid=3338499.3357357>. Acesso em: 25 ago. 2021

PERERA, C. et al. Context Aware Computing for The Internet of Things: A Survey. **IEEE Communications Surveys Tutorials**, v. 16, n. 1, p. 414–454, 2014.

PERERA, C.; VASILAKOS, A. V. A knowledge-based resource discovery for Internet of Things. **Knowledge-Based Systems**, v. 109, p. 122–136, 2016.

PETRAKIS, E. G. M. et al. Internet of Things as a Service (iTaaS): Challenges and solutions for management of sensor data on the cloud and the fog. **Internet of Things (Netherlands)**, v. 3–4, p. 156–174, 2018.

PETRARIU, A. I.; COCA, E.; LAVRIC, A. Large-Scale Internet of Things Multi-Sensor Measurement Node for Smart Grid Enhancement. **Sensors**, v. 21, n. 23, p. 8093, 3 dez. 2021.

PHILIP, J. An application of the dynamic knowledge creation model in big data. **Technology in Society**, v. 54, p. 120–127, ago. 2018.

PHUTTHARAK, J.; LOKE, S. W. A Review of Mobile Crowdsourcing Architectures and Challenges: Toward Crowd-Empowered Internet-of-Things. **IEEE Access**, v. 7, p. 304–324, 2019.

PITT, J.; OBER, J.; DIACONESCU, A. **Knowledge Management Processes and Design Principles for Self-Governing Socio-Technical Systems**. 2017 IEEE 2nd International Workshops on Foundations and Applications of Self* Systems (FAS*W). **Anais**... Em: 2017 IEEE 2ND INTERNATIONAL WORKSHOPS ON FOUNDATIONS AND APPLICATIONS OF SELF* SYSTEMS (FAS*W). set. 2017.

PLIATSIOS, A.; GOUMOPOULOS, C.; KOTIS, K. A Review on IoT Frameworks Supporting Multi-Level Interoperability – The Semantic Social Network of Things Framework. **International Journal on Advances in Internet Technology**, v. 13, n. 1 & 2, p. 46–64, 2020.

POZA-LUJAN, J.-L. et al. Distributed architecture to integrate sensor information: Object recognition for smart cities. **Sensors (Switzerland)**, v. 20, n. 1, 2020.

POZZA, R. et al. Neighbor Discovery for Opportunistic Networking in Internet of Things Scenarios: A Survey. **IEEE Access**, v. 3, p. 1101–1131, 2015.

PRAMANIK, P. K. D. et al. Advancing Modern Healthcare With Nanotechnology, Nanobiosensors, and Internet of Nano Things: Taxonomies, Applications, Architecture, and Challenges. **IEEE Access**, v. 8, p. 65230–65266, 2020.

PRAT, N. A Hierarchical Model for Knowledge Management. Em: **Encyclopedia of Knowledge Management**. Hershey, PA, USA: IGI Global, 2011. v. 1p. 376–388.

PRUTEANU, E.; GABRIEL, P. **Intelligent Measuring System Using Network Wireless Sensors for Structural Diagnostics**. 2019 22nd International Conference on Control Systems and Computer Science (CSCS). **Anais**... Em: 2019 22ND INTERNATIONAL CONFERENCE ON CONTROL SYSTEMS AND COMPUTER SCIENCE (CSCS). maio 2019.

PUNDIR, M.; SANDHU, J. K. A Systematic Review of Quality of Service in Wireless Sensor Networks using Machine Learning: Recent Trend and Future Vision. **Journal of Network and Computer Applications**, v. 188, 2021.

PURRI, S. et al. **Specialization of IoT applications in health care industries**. Proceedings of the 2017 International Conference On Big Data Analytics and Computational Intelligence, ICBDACI 2017. **Anais**...2017. Disponível em: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85040195693&doi=10.1109%2fICBDACI.2017.8070843&partnerID=40&md5=319d82d463c7b1c92499c13980117784>

PÜSCHEL, L.; ROEGLINGER, M.; SCHLOTT, H. What's in a Smart Thing? Development of a Multi-layer Taxonomy. **ICIS 2016 Proceedings**, 11 dez. 2016.

PUTRI, N. K. S.; HUDIARTO; ARGOGALIH. **Knowledge management model for telemedicine**. 2017 International Conference on Information Management and Technology (ICIMTech). **Anais**... Em: 2017 INTERNATIONAL CONFERENCE ON INFORMATION MANAGEMENT AND TECHNOLOGY (ICIMTECH). Yogyakarta: IEEE, nov. 2017. Disponível em: <http://ieeexplore.ieee.org/document/8273525/>. Acesso em: 13 jun. 2019

QANBARI, S. et al. **Gatica: Linked Sensed Data Enrichment and Analytics Middleware for IoT Gateways**. 3rd International Conference on Future Internet of Things and Cloud. **Anais**... Em: 3RD INTERNATIONAL CONFERENCE ON FUTURE INTERNET OF THINGS AND CLOUD. Rome, Italy: 24 ago. 2015.

QIN, C. et al. A Hierarchical Information Acquisition System for AUV Assisted Internet of Underwater Things. **IEEE Access**, v. 8, p. 176089–176100, 2020.

QIU, T. et al. Underwater Internet of Things in Smart Ocean: System Architecture and Open Issues. **IEEE Transactions on Industrial Informatics**, v. 16, n. 7, p. 4297–4307, 2020.

QUEK, Y. T.; WOO, W. L.; LOGENTHIRAN, T. Smart Sensing of Loads in an Extra Low Voltage DC Pico-Grid Using Machine Learning Techniques. **IEEE Sensors Journal**, v. 17, n. 23, p. 7775–7783, dez. 2017.

RAJ, A.; PRAKASH, S. **Internet of Everything: A survey based on Architecture, Issues and Challenges**. 5th IEEE Uttar Pradesh Section International Conference on Electrical, Electronics and Computer Engineering (UPCON). **Anais**... Em: 5TH IEEE UTTAR PRADESH SECTION INTERNATIONAL CONFERENCE ON ELECTRICAL, ELECTRONICS AND COMPUTER ENGINEERING (UPCON). Gorakhpur, India: IEEE, 2 nov. 2018. Disponível em: <https://ieeexplore.ieee.org/document/8596923/>. Acesso em: 31 maio. 2020

RAMAKRISHNA, C. et al. Iot based smart farming using cloud computing and machine learning. **International Journal of Innovative Technology and Exploring Engineering**, v. 9, n. 1, p. 3455–3458, 2019.

RAMÍREZ-MORENO, M. A. et al. Sensors for sustainable smart cities: A review. **Applied Sciences (Switzerland)**, v. 11, n. 17, 2021a.

RAMÍREZ-MORENO, M. A. et al. Sensors for Sustainable Smart Cities: A Review. **Applied Sciences**, v. 11, n. 17, p. 8198, jan. 2021b.

RANA, M. M. IoT-Based Electric Vehicle State Estimation and Control Algorithms under Cyber Attacks. **IEEE Internet of Things Journal**, v. 7, n. 2, p. 874–881, 2020.

RANA, M. M.; BO, R. IoT-based cyber-physical communication architecture: Challenges and research directions. **IET Cyber-Physical Systems: Theory and Applications**, v. 5, n. 1, p. 25–30, 2020.

RAVIGNANI, A. et al. Primate Drum Kit: A System for Studying Acoustic Pattern Production by Non-Human Primates Using Acceleration and Strain Sensors. **Sensors**, v. 13, n. 8, p. 9790–9820, 31 jul. 2013.

RAYES, A.; SALAM, S. The Things in IoT: Sensors and Actuators. Em: RAYES, A.; SALAM, S. (Eds.). . **Internet of Things From Hype to Reality**. Cham: Springer International Publishing, 2017. p. 57–77.

REDDY, R. R.; MAMATHA, C.; REDDY, R. G. **A Review on Machine Learning Trends, Application and Challenges in Internet of Things**. 2018 INTERNATIONAL CONFERENCE ON ADVANCES IN COMPUTING, COMMUNICATIONS AND

INFORMATICS (ICACCI). **Anais**...PES Inst Technol, Bangalore South Campus; IEEE; IEEE Communicat Soc; IEEE Photon Soc; IEEE Robot & Automat Soc, 2018.

RHO, S.; CHEN, Y. Social Internet of Things: Applications, architectures and protocols. **Future Generation Computer Systems**, v. 82, p. 667–668, 1 maio 2018.

RISTESKA STOJKOSKA, B. L.; TRIVODALIEV, K. V. A review of Internet of Things for smart home: Challenges and solutions. **Journal of Cleaner Production**, v. 140, p. 1454–1464, jan. 2017.

RISTOSKI, P.; PAULHEIM, H. Semantic Web in data mining and knowledge discovery: A comprehensive survey. **Journal of Web Semantics**, v. 36, p. 1–22, 1 jan. 2016.

ROMAN, V.; ORDIERES-MERE, J. **IoT Blockchain Technologies for Smart Sensors Based on Raspberry Pi**. Proceedings - IEEE 11th International Conference on Service-Oriented Computing and Applications, SOCA 2018. **Anais**...2019. Disponível em: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85061537725&doi=10.1109%2fSOCA.2018.00038&partnerID=40&md5=17a044262bbf3125bb7b368efd22a322>

RONDON, L. P. et al. **LightningStrike: (in)secure practices of E-IoT systems in the wild**. Proceedings of the 14th ACM Conference on Security and Privacy in Wireless and Mobile Networks. **Anais**... Em: WISEC '21: 14TH ACM CONFERENCE ON SECURITY AND PRIVACY IN WIRELESS AND MOBILE NETWORKS. Abu Dhabi United Arab Emirates: ACM, 28 jun. 2021. Disponível em: <https://dl.acm.org/doi/10.1145/3448300.3467830>. Acesso em: 25 ago. 2021

ROY, S.; CHOWDHURY, C. Integration of Internet of Everything (IoE) with Cloud. Em: BATALLA, J. M. et al. (Eds.). . **Beyond the Internet of Things**. Internet of Things. Cham: Springer International Publishing, 2017. p. 199–222.

ROZSA, V. et al. An Application Domain-Based Taxonomy for IoT Sensors. **Advances in Transdisciplinary Engineering**, IOS Press BV: Amsterdam, The Netherlands. v. 4, n. Transdisciplinary Engineering: Crossing Boundaries, p. 249–258, 3 out. 2016.

RUPPERT, T. et al. Enabling technologies for operator 4.0: A survey. **Applied Sciences (Switzerland)**, v. 8, n. 9, 2018.

RUSNACK, M. R. Innovation in sensing technology and application resources. **Biopreservation and Biobanking**, v. 19, n. 2, p. A24, 2021.

RUSSELL, S. J.; NORVIG, P.; DAVIS, E. **Artificial intelligence: a modern approach**. 3rd ed ed. Upper Saddle River: Prentice Hall, 2016.

RUTA, M. et al. Machine learning in the Internet of Things: A semantic-enhanced approach. **Semantic Web**, v. 10, n. 1, p. 183–204, 28 dez. 2018.

SAAD, E.; ELHOSSEINI, M.; HAIKAL, A. Y. Recent achievements in sensor localization algorithms. **Alexandria Engineering Journal**, v. 57, n. 4, p. 4219–4228, 1 dez. 2018.

SAARIKA, P. S.; SANDHYA, K.; SUDHA, T. **Smart transportation system using IoT**. Proceedings of the 2017 International Conference On Smart Technology for Smart Nation, SmartTechCon 2017. **Anais**...2018. Disponível em: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85048048155&doi=10.1109%2fSmartTechCon.2017.8358540&partnerID=40&md5=b9c2fdefeabab042208761b5468915ed>

SAHINEL, D. et al. **Integration of Human Actors in IoT and CPS Landscape**. IEEE 5th World Forum on Internet of Things (WF-IoT). **Anais**... Em: IEEE 5TH WORLD FORUM ON INTERNET OF THINGS (WF-IOT'19). Limerick, Ireland: IEEE, 15 abr. 2019. Disponível em: <https://ieeexplore.ieee.org/document/8767276/>. Acesso em: 30 out. 2019

SALIM, F.; HAQUE, U. Urban computing in the wild: A survey on large scale participation and citizen engagement with ubiquitous computing, cyber physical systems, and Internet of Things. **International Journal of Human-Computer Studies**, Transdisciplinary Approaches to Urban Computing. v. 81, p. 31–48, 1 set. 2015.

SANGIORGI, D. et al. A Human-Centred, Multidisciplinary, and Transformative Approach to Service Science: A Service Design Perspective. Em: **Handbook of Service Science**. [s.l.] Springer International Publishing, 2019. v. II.

SANTORO, G. et al. The Internet of Things: Building a knowledge management system for open innovation and knowledge management capacity. **Technological Forecasting and Social Change**, mar. 2017.

SCHATTEN, M.; ŠEVA, J.; TOMIČIĆ, I. A roadmap for scalable agent organizations in the Internet of Everything. **Journal of Systems and Software**, v. 115, n. Supplement C, p. 31–41, 1 maio 2016.

SCHEDLER, K.; GUENDUEZ, A. A.; FRISCHKNECHT, R. How smart can government be? Exploring barriers to the adoption of smart government. **Information Polity**, v. 24, n. 1, p. 3–20, 2019.

SEHRAWAT, D.; GILL, N. S. **Smart Sensors: Analysis of Different Types of IoT Sensors**. 2019 3rd International Conference on Trends in Electronics and Informatics (ICOEI). **Anais**... Em: 2019 3RD INTERNATIONAL CONFERENCE ON TRENDS IN ELECTRONICS AND INFORMATICS (ICOEI). abr. 2019.

SERIKUL, P.; NAKPONG, N.; NAKJUATONG, N. **Smart Farm Monitoring via the Blynk IoT Platform : Case Study: Humidity Monitoring and Data Recording**. 2018 16th International Conference on ICT and Knowledge Engineering (ICT&KE). **Anais**... Em: 2018 16TH INTERNATIONAL CONFERENCE ON ICT AND KNOWLEDGE ENGINEERING (ICT&KE). Bangkok: IEEE, nov. 2018. Disponível em: <https://ieeexplore.ieee.org/document/8612441/>. Acesso em: 25 out. 2019

SERROR, M. et al. Challenges and Opportunities in Securing the Industrial Internet of Things. **IEEE Transactions on Industrial Informatics**, v. 17, n. 5, p. 2985–2996, maio 2021.

SETHI, P.; SARANGI, S. R. Internet of Things: Architectures, Protocols, and Applications. **Journal of Electrical and Computer Engineering**, v. 2017, p. 1–25, 2017.

SHAH, S. A. et al. The Rising Role of Big Data Analytics and IoT in Disaster Management: Recent Advances, Taxonomy and Prospects. **IEEE Access**, v. 7, p. 54595–54614, 2019.

SHAHID, N.; ANEJA, S. **Internet of Things: Vision, application areas and research challenges**. International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud) (I-SMAC). **Anais**... Em: INTERNATIONAL CONFERENCE ON I-SMAC (IOT IN SOCIAL, MOBILE, ANALYTICS AND CLOUD) (I-SMAC). Palladam, India: 10 fev. 2017.

SHAO, G.; KIBIRA, D. **Digital manufacturing: Requirements and challenges for implementing digital surrogates**. Proceedings - Winter Simulation Conference. **Anais**...2019. Disponível em: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85062624777&doi=10.1109%2fWSC.2018.8632242&partnerID=40&md5=f20fc589f64defa645e44ff8757867e9>

SHARIQ, S. Z.; VENDELO, M. T. Contexts for Tacit Knowledge Sharing. Em: **Encyclopedia of Knowledge Management**. 2. ed. [s.l.] IGI Global, 2011. v. 2p. 121–129.

SHARMA, A.; CHOUDHURY, T.; KUMAR, P. **Health Monitoring & Management using IoT devices in a Cloud Based Framework**. Proceedings on 2018 International Conference on Advances in Computing and Communication Engineering, ICACCE 2018. **Anais**...2018. Disponível em: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85053452400&doi=10.1109%2fICACCE.2018.8441752&partnerID=40&md5=b4a017a459fd1a4ed10549399af8b44c>

SHARMA, A.; KAUR, R.; YADAV, D. Smart Sensor Technologies for Healthcare Systems. **Internet of Things**, p. 159–180, 2021.

SHARMA, R. et al. **Modeling Abstract Concepts For Internet of Everything: A Cognitive Artificial System**. 2018 13th APCA International Conference on Control and Soft Computing (CONTROLO). **Anais**... Em: 2018 13TH APCA INTERNATIONAL CONFERENCE ON AUTOMATIC CONTROL AND SOFT COMPUTING (CONTROLO). Ponta Delgada: IEEE, jun. 2018. Disponível em: <https://ieeexplore.ieee.org/document/8514540/>. Acesso em: 31 maio. 2020

SHEN, W.; NEWSHAM, G.; GUNAY, B. Leveraging existing occupancy-related data for optimal control of commercial office buildings: A review. **Advanced Engineering Informatics**, v. 33, p. 230–242, 1 ago. 2017.

SHENG, T. J. et al. An Internet of Things Based Smart Waste Management System Using LoRa and Tensorflow Deep Learning Model. **IEEE Access**, v. 8, p. 148793–148811, 2020.

SHIT, R. C. et al. Location of Things (LoT): A Review and Taxonomy of Sensors Localization in IoT Infrastructure. **IEEE Communications Surveys Tutorials**, v. 20, n. 3, p. 2028–2061, thirdquarter 2018.

SHOLLA, S.; NAAZ, R.; CHISHTI, M. A. Ethics Aware Object Oriented Smart City Architecture. **China Communications**, v. 14, n. 5, p. 160–173, maio 2017.

SIEWIOREK, D. et al. **SenSay: a context-aware mobile phone**. Seventh IEEE International Symposium on Wearable Computers. **Anais**... Em: SEVENTH IEEE INTERNATIONAL SYMPOSIUM ON WEARABLE COMPUTERS. White Plains, NY, USA: IEEE, 21 out. 2003. Disponível em: <http://ieeexplore.ieee.org/document/1241422/>. Acesso em: 27 nov. 2019

SILVA, E. F. et al. **IEEE P21451-1-7: Providing More Efficient Network Services over MQTT-SN**. SAS 2019 - 2019 IEEE Sensors Applications Symposium, Conference Proceedings. **Anais**...2019. Disponível em: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85065906519&doi=10.1109%2fSAS.2019.8706107&partnerID=40&md5=6dc2c59bbc495c918a26b3ff2398bda8>

SILVA, M. C. O.; SAMPAIO, J. O.; SOUZA, J. M. **Autonomic Data: Use of Meta Information to Evaluate, Classify and Reallocate Data in a Distributed Environment**. Latin American Autonomic Computing Symposium - LAACS 2008. **Anais**... Em: 3TH LATIN AMERICAN AUTONOMIC COMPUTING SYMPOSIUM. Gramado - RS: 2008.

SILVESTRE-BLANES, J.; SEMPERE-PAYÁ, V.; ALBERO-ALBERO, T. Smart sensor architectures for multimedia sensing in iomt. **Sensors (Switzerland)**, v. 20, n. 5, 2020.

SINCHE, S. et al. A Survey of IoT Management Protocols and Frameworks. **IEEE Communications Surveys & Tutorials**, Secondquarter 2020. v. 22, n. 2, p. 1168–1190, 2019.

SINGA, N. K.; JADHAV, N.; MATHEW, B. Distributed computing using SMART sensors in industrial automation framework. **International Journal of Forensic Software Engineering**, v. 1, n. 2–3, p. 215–230, 1 jan. 2020.

SINGH, K.; SINGH TOMAR, D. D. **Architecture, enabling technologies, security and privacy, and applications of internet of things: A survey**. Proceedings of the International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud), I-SMAC 2018. **Anais**...2019. Disponível em: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85063486942&doi=10.1109%2fI-SMAC.2018.8653708&partnerID=40&md5=e136ec3dfe7f6b0405aa42f6c4b9106b>

SINGLA, K.; BOSE, J. System for user context determination in a network of IoT devices. **Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)**, v. 10898 LNCS, p. 317–323, 2018.

SIOW, E.; TIROPANIS, T.; HALL, W. Analytics for the Internet of Things: A Survey. **ACM Comput. Surv.**, v. 51, n. 4, p. 74:1-74:36, jul. 2018a.

SIOW, E.; TIROPANIS, T.; HALL, W. Analytics for the Internet of Things: A Survey. **ACM Computing Surveys**, v. 51, n. 4, p. 1–36, 25 jul. 2018b.

SMUTNÝ, P. **Different perspectives on classification of the Internet of Things**. 17th International Carpathian Control Conference (ICCC). **Anais**... Em: 17TH INTERNATIONAL CARPATHIAN CONTROL CONFERENCE (ICCC). Tatranska Lomnica, Slovakia: 29 jun. 2016.

SOLANGI, Z. A. et al. **The future of data privacy and security concerns in Internet of Things**. 2018 IEEE International Conference on Innovative Research and Development (ICIRD). **Anais**... Em: 2018 IEEE INTERNATIONAL CONFERENCE ON INNOVATIVE RESEARCH AND DEVELOPMENT (ICIRD). Bangkok: IEEE, maio 2018. Disponível em: <https://ieeexplore.ieee.org/document/8376320/>. Acesso em: 25 out. 2019

SONG, E. Y. et al. **IEEE 1451 Smart Sensor Digital Twin Federation for IoT/CPS Research**. 2019 IEEE Sensors Applications Symposium (SAS). **Anais**...mar. 2019.

SONG, E. Y. et al. A Methodology for Modeling Interoperability of Smart Sensors in Smart Grids. **IEEE Transactions on Smart Grid**, p. 1–1, 2021.

SRINIVAS, K.; JABBAR, M. A.; NEERAJA, K. S. Sensors in IoE: A Review. **International Journal of Engineering & Technology**, v. 7, n. 4.6, p. 158, 25 set. 2018.

SRINIVASAN, C. R. et al. A Review on the Different Types of Internet of Things (IoT). **Control Systems**, v. 11, n. 1, p. 6, 2019.

SRIVASTAVA, G. et al. **An ensemble model for intrusion detection in the Internet of Softwarized Things**. Adjunct Proceedings of the 2021 International Conference on Distributed Computing and Networking. **Anais**... Em: ICDCN ’21: INTERNATIONAL CONFERENCE ON DISTRIBUTED COMPUTING AND NETWORKING 2021. Nara Japan: ACM, 5 jan. 2021. Disponível em: <https://dl.acm.org/doi/10.1145/3427477.3429987>. Acesso em: 25 ago. 2021

STEFANA, E. et al. Wearable Devices for Ergonomics: A Systematic Literature Review. **Sensors**, v. 21, n. 3, p. 777, 24 jan. 2021.

SUBBU, K. P.; VASILAKOS, A. V. Big Data for Context Aware Computing – Perspectives and Challenges. **Big Data Research**, v. 10, p. 33–43, 1 dez. 2017.

SUN, D. et al. Intelligent Data Collaboration in Heterogeneous-device IoT Platforms. **ACM Transactions on Sensor Networks**, v. 17, n. 3, p. 1–17, 21 jun. 2021.

SURESH, A.; UDENDHRAN, R.; BALAMURUGAN, M. Integrating IoT and machine learning – The driving force of industry 4.0. **EAI/Springer Innovations in Communication and Computing**, p. 219–235, 2020.

TAMILSELVI, V. et al. **IoT Based Health Monitoring System**. 2020 6th International Conference on Advanced Computing and Communication Systems, ICACCS 2020. **Anais**...2020. Disponível em: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85084660604&doi=10.1109%2fICACCS48705.2020.9074192&partnerID=40&md5=50ae4c205d78af01d56acd05ef1b74dd>

TAN, P. J. B. An Empirical Study of How the Learning Attitudes of College Students toward English E-Tutoring Websites Affect Site Sustainability. **SUSTAINABILITY**, v. 11, n. 6, 22 mar. 2019.

TANG, Y.; WANG, D. Optimization of Sports Fitness Management System Based on Internet of Health Things. **IEEE Access**, v. 8, p. 209556–209569, 2020.

TAYLOR, W. et al. A Review of the State of the Art in Non-Contact Sensing for COVID-19. **Sensors**, v. 20, n. 19, p. 5665, 3 out. 2020.

TENG, H. et al. A novel code data dissemination scheme for Internet of Things through mobile vehicle of smart cities. **Future Generation Computer Systems**, v. 94, p. 351–367, 2019.

TERRES, L. et al. **Autonomic Business Process Simulation in a Rock Analysis Laboratory**. 15 set. 2008.

TSAI, C. et al. Data Mining for Internet of Things: A Survey. **IEEE Communications Surveys Tutorials**, v. 16, n. 1, p. 77–97, First 2014.

TURCHET, L. Smart Musical Instruments: Vision, Design Principles, and Future Directions. **IEEE Access**, v. 7, p. 8944–8963, 2019.

ULLO, S. L.; SINHA, G. R. Advances in smart environment monitoring systems using iot and sensors. **Sensors (Switzerland)**, v. 20, n. 11, 2020.

UR REHMAN, M. H. UR et al. Towards next-generation heterogeneous mobile data stream mining applications: Opportunities, challenges, and future research directions. **Journal of Network and Computer Applications**, v. 79, p. 1–24, fev. 2017.

URBINA, M. et al. Smart Sensor: SoC Architecture for the Industrial Internet of Things. **IEEE Internet of Things Journal**, v. 6, n. 4, p. 6567–6577, ago. 2019.

USCHOLD, M. ; G. Ontologies: Principles, Methods and Applications. **Knowledge Engineering Review**, v. 11, n. 2, p. 93–155, 1996.

VANDEBROEK, S. V. **1.2 Three pillars enabling the Internet of Everything: Smart everyday objects, information-centric networks, and automated real-time insights**. IEEE International Solid-State Circuits Conference (ISSCC). **Anais**... Em: IEEE INTERNATIONAL SOLID-STATE CIRCUITS CONFERENCE (ISSCC). San Francisco, CA, USA: IEEE, 31 fev. 2016. Disponível em: <http://ieeexplore.ieee.org/document/7417889/>. Acesso em: 31 maio. 2020

VAYA, D.; HADPAWAT, T. Internet of everything (IoE): A new era of IoT. **Lecture Notes in Electrical Engineering**, v. 570, p. 1–6, 2020.

VENABLE, J.; PRIES-HEJE, J.; BASKERVILLE, R. FEDS: a Framework for Evaluation in Design Science Research. **European Journal of Information Systems**, v. 25, n. 1, p. 77–89, jan. 2016.

VISHNU, S.; JINO RAMSON, S. R.; JEGAN, R. **Internet of Medical Things (IoMT)-An overview**. ICDCS 2020 - 2020 5th International Conference on Devices, Circuits and Systems. **Anais**...2020. Disponível em: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85084636204&doi=10.1109%2fICDCS48716.2020.243558&partnerID=40&md5=aaaac7ac5bef2016d90ec2b572cb1a99>

VITAL, L. P.; CAFÉ, L. M. A. Ontologias e taxonomias: diferenças. **Perspectivas em Ciência da Informação**, v. 16, n. 2, p. 115–130, jun. 2011.

VOICU, V.; PETREUS, D.; ETZ, R. **IoT Blockchain for Smart Sensors**. 2020 43RD INTERNATIONAL SPRING SEMINAR ON ELECTRONICS TECHNOLOGY (ISSE). **Anais**...: International Spring Seminar on Electronics Technology ISSE.2020.

VU, B. et al. **Supporting Taxonomy Management and Evolution in a Web-based Knowledge Management System**. . Em: PROCEEDINGS OF THE 32ND INTERNATIONAL BCS HUMAN COMPUTER INTERACTION CONFERENCE. 1 jul. 2018. Disponível em: <https://scienceopen.com/document?vid=136525d3-0b41-4f3d-953d-0f938ca2a810>. Acesso em: 3 mar. 2021

WANG, J. et al. Building an Improved Internet of Things Smart Sensor Network Based on a Three-Phase Methodology. **IEEE Access**, v. 7, p. 141728–141737, 2019.

WANG, J. et al. Unobtrusive Health Monitoring in Private Spaces: The Smart Vehicle. **Sensors**, v. 20, n. 9, p. 2442, 25 abr. 2020.

WASON, V.; KUMAR, R.; JOHRI, P. **Smart Sensors Network using IoT technologies**. 2021 International Conference on Advance Computing and Innovative Technologies in Engineering, ICACITE 2021. **Anais**...2021. Disponível em: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85104995363&doi=10.1109%2fICACITE51222.2021.9404746&partnerID=40&md5=664a6acfe81c52502e8929ab165760a4>

WAZID, M. et al. **Private blockchain-envisioned security framework for AI-enabled IoT-based drone-aided healthcare services**. Proceedings of the 2nd ACM MobiCom Workshop on Drone Assisted Wireless Communications for 5G and Beyond. **Anais**...: DroneCom ’20.New York, NY, USA: Association for Computing Machinery, 25 set. 2020. Disponível em: <http://doi.org/10.1145/3414045.3415941>. Acesso em: 25 ago. 2021

WEI, L. et al. On Designing Context-Aware Trust Model and Service Delegation for Social Internet of Things. **IEEE Internet of Things Journal**, v. 8, n. 6, p. 4775–4787, mar. 2021.

WHITMORE, A.; AGARWAL, A.; XU, L. D. The Internet of Things—A survey of topics and trends. **Information Systems Frontiers**, v. 17, n. 2, p. 261–274, 1 abr. 2015.

WIGGINS, A. **eBirding: technology adoption and the transformation of leisure into science**. Proceedings of the 2011 iConference on - iConference ’11. **Anais**... Em: THE 2011 ICONFERENCE. Seattle, Washington: ACM Press, 8 fev. 2011. Disponível em: <http://portal.acm.org/citation.cfm?doid=1940761.1940910>. Acesso em: 11 nov. 2020

WU, Z.; CHENG, T.; WANG, Z. L. Self-Powered Sensors and Systems Based on Nanogenerators. **Sensors**, v. 20, n. 10, p. 2925, 21 maio 2020.

XU, R. et al. **A federated capability-based access control mechanism for internet of things (IoTs)**. Proceedings of SPIE - The International Society for Optical Engineering. **Anais**...2018. Disponível em: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85048399873&doi=10.1117%2f12.2305619&partnerID=40&md5=f01f511ab43bc44c6bd7647a2690cdcf>

XU, T.; ZHOU, Y.; ZHU, J. New advances and challenges of fall detection systems: A survey. **Applied Sciences (Switzerland)**, v. 8, n. 3, 2018.

YAMINI, G.; GANAPATHY, G. An Internet of Things Inspired Approach for Enhancing Reliability in Healthcare Monitoring. **EAI/Springer Innovations in Communication and Computing**, p. 155–168, 2021.

YANG, C. et al. Big-Sensing-Data Curation for the Cloud is Coming: A Promise of Scalable Cloud-Data-Center Mitigation for Next-Generation IoT and Wireless Sensor Networks. **IEEE Consumer Electronics Magazine**, v. 6, n. 4, p. 48–56, 2017.

YANG, J.; SHARMA, A.; KUMAR, R. IoT-based framework for smart agriculture. **International Journal of Agricultural and Environmental Information Systems**, v. 12, n. 2, p. 1–14, 2021.

YANG, L. T.; DI MARTINO, B.; ZHANG, Q. Internet of Everything. **Mobile Information Systems**, v. 2017, p. 1–3, 2017.

YANG, S.; WEI, R. Tabdoc approach: An information fusion method to implement semantic interoperability between IoT devices and users. **IEEE Internet of Things Journal**, v. 6, n. 2, p. 1972–1986, 2019.

YANG, X. et al. Parallel Computing for Efficient and Intelligent Industrial Internet of Health Things: An Overview. **Complexity**, v. 2021, 2021.

YAQOOB, I. et al. Big data: From beginning to future. **International Journal of Information Management**, v. 36, n. 6, Part B, p. 1231–1247, 1 dez. 2016.

YAQOOB, I. et al. Internet of Things Architecture: Recent Advances, Taxonomy, Requirements, and Open Challenges. **IEEE Wireless Communications**, v. 24, n. 3, p. 10–16, jun. 2017.

YASEER, A.; CHEN, H. **A Review of Sensors and Machine Learning in Animal Farming**. 2021 IEEE 11th Annual International Conference on CYBER Technology in Automation, Control, and Intelligent Systems, CYBER 2021. **Anais**...2021. Disponível em: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85119376177&doi=10.1109%2fCYBER53097.2021.9588295&partnerID=40&md5=d6c5549e3d47f2c6abd0b4ae7f618b35>

YEBDA, T. et al. **Multi-sensing of fragile persons for risk situation detection: devices, methods, challenges**. International Conference on Content-Based Multimedia Indexing (CBMI). **Anais**... Em: INTERNATIONAL CONFERENCE ON CONTENT-BASED MULTIMEDIA INDEXING (CBMI). Dublin, Ireland: IEEE, 4 set. 2019. Disponível em: <https://ieeexplore.ieee.org/document/8877476/>. Acesso em: 30 out. 2019

YEH, W.-C.; LIN, J.-S. New parallel swarm algorithm for smart sensor systems redundancy allocation problems in the Internet of Things. **Journal of Supercomputing**, v. 74, n. 9, p. 4358–4384, 2018.

YIN, H.; WANG, Z.; JHA, N. K. A hierarchical inference model for internet-of-things. **IEEE Transactions on Multi-Scale Computing Systems**, v. 4, n. 3, p. 260–271, 2018.

YOU, S.; LI, X.; CHEN, W. **A semantic mechanism for Internet-of-Things (IoT) to implement intelligent interactions**. 2018 16th International Symposium on Modeling and Optimization in Mobile, Ad Hoc, and Wireless Networks (WiOpt). **Anais**... Em: 2018 16TH INTERNATIONAL SYMPOSIUM ON MODELING AND OPTIMIZATION IN MOBILE, AD HOC, AND WIRELESS NETWORKS (WIOPT). maio 2018.

YOUNIS, M. Internet of everything and everybody: Architecture and service virtualization. **Computer Communications**, v. 131, p. 66–72, 2018.

YU, J. et al. **A Framework on Semantic Thing Retrieval Method in IoT and IoE Environment**. International Conference on Platform Technology and Service (PlatCon). **Anais**... Em: INTERNATIONAL CONFERENCE ON PLATFORM TECHNOLOGY AND SERVICE (PLATCON). Jeju, Korea: IEEE, 29 jan. 2018.

YU, W. et al. A Survey on the Edge Computing for the Internet of Things. **IEEE Access**, v. 6, p. 6900–6919, 2017.

YUAN, L. et al. Research on key technologies of human-machine-environment states perception in mine Internet of things [矿山物联网人-机-环状态感知关键技术研究]. **Tongxin Xuebao/Journal on Communications**, v. 41, n. 2, p. 1–12, 2020.

ZHANG, J. et al. Data Security and Privacy-Preserving in Edge Computing Paradigm: Survey and Open Issues. **IEEE Access**, v. 6, p. 18209–18237, 2018.

ZHANG, T. et al. Self-learning soft computing algorithms for prediction machines of estimating crowd density. **Applied Soft Computing**, v. 105, 2021.

ZHILENKOV, A. A. et al. **Power line communication in IoT-systems**. Proceedings of the 2017 IEEE Russia Section Young Researchers in Electrical and Electronic Engineering Conference, ElConRus 2017. **Anais**...2017. Disponível em: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85019479309&doi=10.1109%2fEIConRus.2017.7910538&partnerID=40&md5=3d3e964720accf024e6d35ebb4fe037b>