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THE INTERNET OF THINGS INNOVATIONS: AN ANALYSIS THROUGH A MULTI-METHOD APPROACH ON CUSTOMER ADOPTION AND RESISTANCE FACTORS

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Alla mia famiglia,
per il loro infinito amore e fondamentale supporto.
Alla LUISS,
per il ricco bagaglio, carico non solo di conoscenze accademiche,
con cui terminerò questo percorso meraviglioso.
Ed infine a me,
per la costante determinazione ed instancabile forza di volontà.

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Introduction

The widespread phenomenon of the Internet of Things (IoT) represents a new phase in the Internet revolution emerged in the Information Technology field that, over the last decade, has led to a total paradigm shift in the world of computing and communication. It refers to a world in which, through the Internet, the interconnection of objects around us, the interaction between them and humans as well as the continuous exchange of data will become more and more common in our lives as to become a fundamental part of it. Even if the idea of connecting objects to each other and to the Internet is not new, the phenomenon of the Internet of Things (IoT) has grown fast in the latest years driven by a convergence of various advanced technologies with new emerging computing and connectivity trends and the development of three important related phenomena, namely Big Data, Machine Learning and Cloud Computing.

The Internet of Things (IoT) brings the intelligence of the Internet to physical products, known as *Smart Objects*. Specifically, these devices are able to collect, aggregate and analyse a significant amount of data, interact and communicate with each other and with humans and activate actions instantaneously and autonomously. A strategic and accurate analysis of the data collected enables companies to extract meaningful and valuable insights and gain a better understanding of their customers as to deliver more relevant and personalized offerings. Therefore, companies able to organize, analyse and extract relevant information from their database can benefit of a significant competitive advantage. New business opportunities have also emerged by integrating these technological objects into the development of new services, known as *Smart Services*, mainly characterized by an automation of tasks.

Over the last decade, smart products and smart services have grown steadily with applications in different domains. Based on the forecasts of *Business Insider Intelligence,* by 2026 there will be more than 64 billion devices connected to the Internet, with consumers and companies spending around $15 trillion over them, their solutions and supporting systems. The myriad of applications can be extended to almost every aspect of everyday life of individuals, companies and society as a whole, improving the quality of lives in many different sectors and environments.

Smart objects can be considered as building blocks of the Internet of Things (IoT). They are seen as radical and revolutionary transformation of the original product and smart services as a new way of benefiting from traditional services: they are both perceived by customers as something different and new. Therefore, given the main characteristics of smart objects and smart services and the intense impact they have on customers' live, they can be considered not only as simple innovations but even as disruptive innovations. However, Roger's process of innovation diffusion and its success do not have to be taken for granted. As a matter of fact, the slow pace of customer adoption of new technologies is one of the biggest issues in the Internet of Things (IoT) industry. Most of new smart products and services, once launched on the market, do not become commercially successful. Therefore, understanding which are the factors that cause both customers' resistance and adoption in the specific IoT context is critical to develop and market successfully new products and services, since it has significant implications for businesses.

Chapter 1 introduces the Internet of Things (IoT) phenomenon, in order to provide the theoretical tools to comprehend this revolution, its origin, features, drivers, enabling technologies, architectures and applications. Chapter 2 provides a literature overview on the concept of customer innovation adoption and innovation resistance. However, after a brief introduction to the concept of innovation and innovation adoption, a greater consideration is given to customer resistance. Specifically, after having introduced the theoretical fundaments to comprehend this concept by reviewing the most relevant academic contributions in this field, the discussion continues by describing the major models developed over the past years to further investigate customer resistance to innovations and its determinants. The main theoretical models in the existing literature I have chosen to examine are the *Model of Innovation Resistance* (Ram, 1987), the *Consumer Resistance to Innovations Model* (Ram & Sheth, 1989) and the *Customer Resistance to, and Acceptance of, Innovation Model* (Bagozzi & Lee, 1991). Since the focus of this study is the Internet of Things (IoT) and its smart applications, more attention is given to Ram and Sheth's (1989) model, its extensions, applications and related findings that are particularly relevant to better comprehend customer barriers towards smart products and smart services. Chapter 3, finally, after a brief introduction to Text Mining, Opinion Mining, Natural Language Processing (NLP), Artificial Intelligence (AI) and Machine Learning concepts, proposes two methods of analysis: *sentiment analysis* and *content analysis*. These respectively quantitative and qualitative approaches to textual analysis aim at interpreting and understanding the information contained in the dataset composed of 156 interviews, collected by applying the Critical Incident Technique (CIT). The purpose was to extract valuable insights in order to provide a greater clarity on the nature of the factors of innovation adoption and innovation resistance in the specific IoT context and to identify, quantify and classify customers' emotions towards such innovation.

Chapter I

The Internet of Things (IoT)

The purpose of this chapter is to provide the theoretical tools to comprehend the phenomenon of the Internet of Things (IoT), whose applications will be the subject of analysis in this work. After having introduced, in Section 1.1, the IoT phenomenon and having gone through the multiple definitions that have been given over the years, its origins are traced in Section 1.2. Section 1.3 discusses the seven key IoT attributes and fundamental elements. It is critical to highlight that the functioning of the complex infrastructure of the Internet of Things (IoT) does not depend on one single technology and the multiple IoT enabling technologies are grouped in three different categories presented in Section 1.4. Section 1.5 explains that the architecture of the Internet of Things (IoT) is not defined in a unique way by the whole world of researchers. Over the years, the latter have proposed different architecture structures, namely three-layer architecture, four-layer architecture and five-layer architecture which are described respectively in Section 1.5.1, 1.5.2 and 1.5.3. The Internet of Things (IoT) brings the intelligence of the Internet to physical products, known as *Smart Objects*. New business opportunities have emerged by integrating these technological objects into the development of new services, known as *Smart Services.* Smart objects and smart services definition and features are illustrated in Section 1.6. As seen in Section 1.7, applications and opportunities to use the Internet of Thing are numerous and diverse. They can be extended to almost every aspects of every-day life of individuals, companies and society as a whole, improving the quality of lives in many different sectors and environments. Specifically, literature classifies the environments in which these advanced smart solutions can be applied into the following four domains: *Transportation and industrial IoT domain* (Section 1.7.1), *Healthcare domain* (Section 1.7.2), *Smart environment domain* (Section 1.7.3) and *Personal and social domain* (Section 1.7.4). The last Section 1.8 provides a market overview of the IoT phenomenon. Section 1.8.1 introduces the IoT market drivers and three related phenomena, namely Big Data, Machine Learning and Artificial Intelligence. After having defined the concept of the Internet of Things (IoT), having identified its main features, enabling technologies, architectures, multiple applications, drivers and related phenomena, the impact it has on the market in terms of volume and value is illustrated in Section 1.8.2.

1.1 The Internet of Things (IoT): *Definitions*

"The Internet will disappear. There will be so many IP addresses, so many devices, sensors, things that you are wearing, things that you are interacting with, that you won't even sense it. It will be

part of your presence all the time. Imagine you walk into a room, and the room is dynamic. And with your permission and all of that, you are interacting with the things going on in the room."

The above statement was quoted by Eric Schmidt, Chairman at Google, when asked about the future of the web on a panel called "The Future of the Digital Economy" at the World Economic Forum in Davos, Switzerland, in 2015. The scenario described depicts a new phase in the Internet revolution, in which the interconnection of objects around us, the interaction between them and humans as well as the continuous exchange of data will become more and more common in our lives as to become a fundamental part of it. This revolution has emerged in the Information Technology field and has led to a total paradigm shift in the world of computing and communication. This phenomenon is the so-called *Internet of Things* (IoT) (Madakam et al., 2015, Patel et al., 2016).

The phrase *Internet of Things* comes from the combination of two words: Internet and Things. *Internet* is defined as a global computer network than can be accessed by multiple devices (computer, mobile telephone, digital TV etc.) based on the standard protocol suite (TPC/IP) and provided through a fixed (wired) or mobile network (Madakam et al., 2015) that connects individuals to information (Hussein, 2019). Nowadays, Internet connects hundreds of countries around the world enabling an exchange of data, opinions and news. According to the Internet Live Stats, at the beginning of 2020 there were 4,489,196,040 internet users, defined as "*individual who can access the Internet at home via any device and connection",* in the world. Therefore, almost the 60% of the world population has an internet connection.[1] For what concern the word *Things*, it refers to any distinguishable object by the real and material world of all type and size including both technologically advanced products and those that are not considered as electronic devices such as food, clothing, materials, monuments and works of art (Madakam et al., 2015). There is not a single universally accepted definition for this revolution, mainly because of its evolving nature (Aggarwal et al., 2012). The Internet of Things (IoT) concept was introduced for the first time by Kevin Ashton, a member of the Radio Frequency Identification (RFID) development community, in 1999 (Aggarwal et al., 2012). This British technology pioneer defined it as a network that connects not only individuals but also the objects around them (Patel et al., 2016). At the time, scholars interpreted this statement as something unrealistic. However, today, thanks to technological advances, such as machine-to-machine communication, the Internet of Things (IoT) has become reality. In the following years, different groups of academicians, researchers, developers, innovators and corporate people conducted a lot of research that led to the conception of different definitions (Karen et. al., 2015, Kosmatos et al., 2011).

[1] *InternetLiveStats,com*, Available at: https://www.internetlivestats.com/internet-users/#sources [accessed 29/02/2020]

The latter do not contradict each other, but simply focus on different characteristics of the IoT phenomenon and look at it from different perspectives.

The Internet Architecture Board (IAB) begins RFC 7452, "Architectural Considerations in Smart Object Networking" [2], by providing the following definition:

"The term "Internet of Things" (IoT) denotes a trend where a large number of embedded devices employ communication services offered by the Internet protocols. Many of these devices, often called "smart objects" are not directly operated by humans, but exist as components in buildings or vehicles, or are spread out in the environment."

The Internet Engineering Task Force (IETF) refers to the Internet of Things (IoT) by using the term "Smart object networking", defined as networked devices with constrained memory, processing resources, and bandwidth. [3] The International Telecommunication Union (ITU) in the "ITU–T Recommendation Y.2060, Overview of the Internet of things"[4], published in 2012, expresses itself around the concept of interconnectivity:

"Internet of things (IoT): A global infrastructure for the information society, enabling advanced services by interconnecting (physical and virtual) things based on existing and evolving interoperable information and communication technologies.

Note 1—Through the exploitation of identification, data capture, processing and communication capabilities, the IoT makes full use of things to offer services to all kinds of applications, whilst ensuring that security and privacy requirements are fulfilled.

Note 2—From a broader perspective, the IoT can be perceived as a vision with technological and societal implications."

The IoT is linked back to cloud services in an IEEE Communications Magazine[5] issue that states:

"The Internet of Things (IoT) is a framework in which all things have a representation and a presence in the Internet. More specifically, the Internet of Things aims at offering new applications and services bridging the physical and virtual worlds, in which Machine-to-Machine (M2M)

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[2] Tschofenig, H., Ldr,. A., Thaler, D., McPherson, D. (2015). *Architectural Considerations in Smart Object Networking.* Internet Architecture Board (IAB) RFC 7452, N. 2070-1721.

[3] Thaler, D., Tschofenig, H., Barnes, M. (2015). *Architectural Considerations in Smart Object Networking.* IETF 92 Technical Plenary - IAB RFC 7452.

[4] *Overview of the Internet of Things* (2012). ITU - TELECOMMUNICATION STANDARDIZATION SECTOR OF ITU. Available at: http://www.itu.int/ITU-T/recommendations/rec.aspx?rec=Y.2060 [accessed 06/03/2020].

[5] *Comsoc.org:* http://www.comsoc.org/commag/cfp/internet-thingsm2m-research-standards-next-steps [accessed 06/03/2020]

communications represents the baseline communication that enables the interactions between Things and applications in the cloud."

Lastly, the Oxford Dictionaries[6] defines it as:

"The interconnection via the Internet of computing devices embedded in everyday objects, enabling them to send and receive data."

Therefore, the Internet of Things (IoT) is an open and comprehensive network of intelligent and distinctively addressable physical objects with various degree of processing, sensing and actuation capabilities that have the capacity to auto-organize, share information, data and resources, reacting and acting in face of situations and changes in the environment all interconnected over public or private Internet Protocol (IP) network or Transport control protocol (TCP/IP). This phenomenon connects objects with other objects and individuals at any time and any place, enabling the projection of a global networked infrastructure to create new advanced applications and services. It is also a solid base for planning, management and decision making in order to reach multiple goals (Kosmatos et al., 2011, Hussein, 2019, Patel et al., 2016). Each of these definitions originates from the idea that the Internet was initially based on data created by people, whereas with the Internet of Things (IoT) data are created by a constellation of objects, devices, sensors and other everyday items with network connectivity and computing capabilities (Kosmatos et al., 2011).

1.2 The Internet of Things (IoT): *Origins*

After having introduced the IoT phenomenon and having gone through the multiple definitions that have been given over the years, it is important to trace its origins.

The widespread and popular term "Internet of Things" has its roots in 1999. The term was introduced for the first time by Kevin Ashton, a British technology pioneer, to describe a system in which real-world objects in the field of corporate supply chains could be equipped with Radio Frequency Identification (RFID) tags and sensors connected to the Internet to monitor the movement of raw materials (Vermesan et al., 2014). Although the term is relatively recent, the idea of connecting computers and networks to control devices dates back to late 1970. At that time, these systems were used for commercial purposes to remotely monitor meters on the electrical grid via telephone lines. Later, in 1990, developments in wireless technology enabled the creation and deployment of machine-to-machine (M2M) business and industrial solutions, many of which, however, are not based on Internet Protocol (IP) and Internet standards, but on ad hoc closed networks and proprietary or

[6] *Internet of Things*, Oxford Dictionaries online. Available at: https://www.lexico.com/definition/internet_of_things [accessed 06/03/2020]

industry-specific standards (Vermesan et al., 2014). The first IP-enabled device was introduced in 1990 during a conference. The object presented was a toaster capable of switching on and off thank to the Internet connection. Later, the use of IP to connect devices to the Internet was applied to other objects: a soda machine at Carnegie Mellon University in the US and a coffee pot in the Trojan Room at the University of Cambridge in the UK (Vermesan et al., 2014). In the following years, the research in the field of "smart object networking" has continued enabling to create a solid literature base (Vermesan et al., 2014).

1.3 The Internet of Things (IoT): *Distinctive features*

To have a better understanding of the IoT phenomenon, it is useful to list its distinctive features. The literature identify the following seven key attributers that characterize the Internet of Things (IoT) (Vermesan et al., 2014):

1. *Interconnectivity:* anything can be interconnected by using a global communication and information infrastructure.
2. *Things-related services:* it contributes to the creation of thing-related services within the constraints of privacy protection and semantic consistency between physical things and their associated virtual object.
3. *Heterogeneity:* since the devices are based on different hardware platform and networks they are considered as heterogonous.
4. *Dynamic:* the number of devices can change dynamically as well as their state (location, speed, connection etc.).
5. *Enormous scale:* the number of devices that need to be managed and that communicate with each other will be at least an order of magnitude larger than the devices connected to the current Internet. Indeed, the relationship between the communication triggered by the devices with respect to the communication triggered by humans will shift significantly towards the one triggered by the devices.
6. *Safety:* it has to be incorporated in the design of the IoT infrastructure. It refers to the protection of our personal data and of our physical conditions. It is critical to create a secure infrastructure for what concern the endpoints, networks and data moving across all of it.
7. *Connectivity:* this feature enable all devices to access the network and be compatible for communication and, therefore, produce and exchange data.

Moreover, the Internet of Things (IoT) requires the presence of the following fundamental elements: *things* or *devices* with sensors or sensing materials attached to them; *data* generated and exchanged by the smart devices; *connection* between the devices; *communication* of data over short or long distances; *intelligence* of the devices gathered from big data analytics and artificial intelligence; *actions* that can me manual or automatic as a consequence of intelligence; *ecosystem* that is the broader place in which the IoT fits and includes other technologies, communities and goals.[7]

1.4 The Internet of Things (IoT): *Enabling technologies*

The functioning of the complex infrastructure of the Internet of Things (IoT) does not depend on one single technology. The solutions it provides result from the integration of many Information and Communication technologies. The first group includes hardware and software able to capture, collect and process information. The second one includes the systems used for communication activities between individuals (Patel et al., 2016). The enabling technologies for the Internet of Things (IoT), defined as *technologies that make the IoT applications possible*, such as sensor networks, M2M, semantic data integration, IPv6 and RFID, (Vermesan et al., 2013) can be categorized into three different groups (Vermesan et al., 2014):

1. Technologies that enable the “thing” to capture and collect information from their activity and the environment surrounding them.
2. Technologies that enable the “thing” to process the information collected.
3. Technologies that enable the information collected to be secure and kept private.

Whereas the first two categories of enabling technologies are considered “functional blocks” that make the “thing” intelligent and are the main feature that differentiates the IoT from the usual Internet; the last category has nothing to do with the functioning of the device, but rather with its market penetration. Indeed, the latter would be greatly reduced by a lack of attention to the requirements of privacy and security (Vermesan et al., 2014). The development of the Internet of Things (IoT) and its rapid growth requires that these enabling technologies have fundamental features, like a very high data transmission speed, the ability to handle large crowds of users, a low power consumption and a low cost and efficient connection of a large number of devices (Vermesan et al., 2014). Specific enabling technologies are mentioned in Section 1.5 below while describing the three Internet of Things (IoT) architectures.

1.5 The Internet of Things (IoT): *Architectures*

The architecture of the Internet of Things (IoT) is not defined in a unique way by the whole world of researchers. Over the years, the latter have proposed different architecture structures. However, it is universally agreed that the IoT structure is divided into multiple layers. According to some, the

[7] *I-scoop.eu:* https://www.i-scoop.eu/internet-of-things-guide/iot-definitions/ [accessed 3/03/2020]

architecture has only three layers, while others argue that it has four or even five layers. It is believed that the three-layer architecture could meet the requirements of Internet of Things (IoT) applications only in a primordial state. For this reason, with its rapid development and the emergence of new challenges, especially in terms of security and privacy, new additional layers had to be added to the architecture structure (Burhan et al., 2018).

1.5.1 *Three Layer Architecture*

The three layer architecture was proposed in the early stages of development of the IoT phenomenon and it is the most basic structure. It is composed of three layers (Burhan et al., 2018):

1. *Perception layer:* also known as *sensor layer,* it includes all those technologies that enable objects to become "smart" and, therefore, to be interconnected, collect and process real-time information about the environment or about other connected devices through sensors. The various types of sensors can be categorized according to their purpose: environmental sensors, body sensors, home appliance sensors, vehicle telematics sensors etc. Some sensors may require connectivity to the sensor gateway and this can happen in the form of a Local Area Network (LAN) (Ethernet, WI-FI connections) or Personal Area Network (PAN) (ZigBee, Bluetooth, Ultra Wideband). Some others do not need any connection to sensor aggregators and their connectivity is provided by Wide Area Network (WAN) (GSM, GPRS, LTE). Lately, a new form of network, known as Wireless Sensor Networks (WSNs), has gained popularity. This kind of network is formed by sensors that use low power and low data rate connectivity. They can connect more sensor nodes with low battery consumption while covering large areas. (Patel et al., 2016) Through sensors, we can acquire a large amount of information from the physical world. However, we may only be interested in some of them. Through this layer, the physical world can be represented by a personalized information system, namely the *P system,* that is able to detect only the relevant data. In the P system, two categories of information are mainly collected, namely *customized environmental information* and *user profile*. The user profile contains ID, vital information, capacity, location, interest, behaviour and P-score. (Min, 2013)
2. *Network Layer:* also known as *transmission layer*, since it has the function to transmit the massive volume of data collected by sensors through a robust wired or wireless network infrastructure as mean. It connects the perception layer to the application layer. It is also responsible for connecting smart objects, network devices and networks to each other (Burhan et al., 2018, Patel et al., 2016). The technologies that enable the functioning of this layer are wireless technologies such as Wireless Sensor Network (WSNs), Body Area Network

(BANs), Bluetooth, Mobile Phone Line (3G, 4G). However, the most widely used is Wi-Fi, which allows user terminals to connect to each other via a Wireless Local Area Network (WLAN). Consequently, the local network created can be connected to the Internet via a router and take advantage of all the connectivity services offered by the provider (Chan, 2015).

3. *Application Layer:* this layer includes all the applications whose functioning depends on the IoT technology, such as "smart" environments in the domain of transportation, city, building, retail, emergency, healthcare, culture, environment, energy, tourism, lifestyle and agriculture (Burhan et al., 2018, Patel et al., 2016). Application layer should provide fast service responses to the user and to physical phenomena based on the use of intelligent decision-making algorithms integrated in software application. It is made possible by analysing the latest information about physical entities or by taking into account patterns found by the analysis of historical data (Min., 2013).

1.5.2 *Four-Layer Architecture*

The three-layer architecture is the most basic structure. The rapid development and growth of the Internet of Things (Io) has led researchers to propose a four layer architecture to ensure that the IoT continues to meet all requirements, especially in terms of privacy and security. This new architecture is composed of exactly the same three layers described above, to which a fourth layer is added (Burhan et al., 2018):

4. *Support Layer:* this layer deals with the processing of information produced by sensors and shared by networks (Chan, 2015) through analytics, security controls, process modelling and management of devices (Patel et al., 2016). It was created to ensure security in the IoT architecture. Indeed, in the three-layer architecture the information is sent directly to the network layer. This is a risky operation from the point of view of data protection. Instead, in the four-layer architecture, the information is first sent to the support layer, which has a dual task. The first one consists into ensuring that the data are sent by an authentic user and protected from possible external threats, through various methods. One of these is the *authentication* guaranteed by using pre-shared keys and passwords. The second task consists into sending information to the network layer via wireless or wire based methods (Burhan et al., 2018). The main technology enabling the functioning of this layer is cloud computing, which will be described in more details in Section 1.8.1. Within the cloud resides the analytical component, the heart of the IoT structure, in which the algorithms have the

fundamental role of performing the computational and decision-making processes in order to achieve the objectives set for the system. The decisions result in actions send to the actuators to be executed or in outcomes shown in the user interfaces to allow the end user to make informed decisions about the state of the environment. Moreover, within this layer, in the area or analytics, relevant information are extracted from a huge amount of raw data and then processed through the use of multiple tools such as: in-memory analytics, that enable large volumes of data to be collected in random access memory (RAM) rather than in physical disks thus augmenting the speed of decision making, and streaming analytics. This enables the analysis of data-in-motion, it means that the analysis is carried out in real time and decisions are made in few seconds. This layer also includes the data management activity, which consists into managing data information flow. It means that information can be accessed, integrated and controlled. To enhance the efficiency of the functioning of the higher application layer, data filtering techniques such as data anonymization, data integration and data synchronization are employed by this layer to provide only the relevant information to the related application while protecting the most private details (Patel et al., 2016).

The whole IoT architecture, from the first to the fourth layer, must guarantee the respect of security and privacy requirements, in order to prevent from threats and risks such as system hacking from unauthorized individuals (Patel et al., 2016).

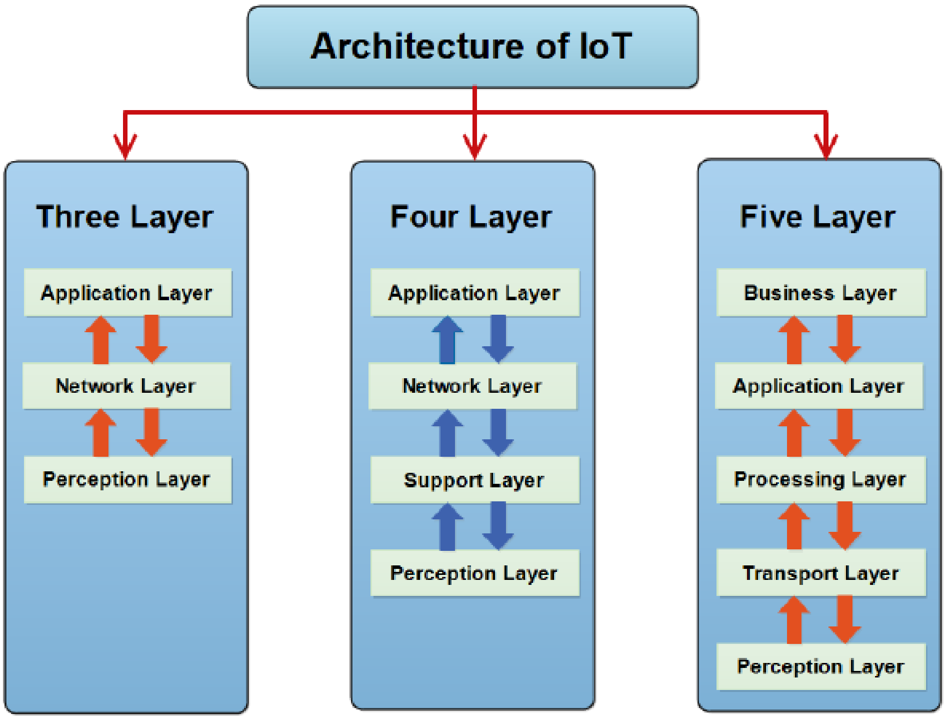
1.5.3 *Five Layer Architecture*

Later, although the four layer architecture represents an improvement in terms of security and privacy of information, a new structure made up of five layers was introduced. The latter consists of a perception layer, a transport layer and an application layer, which are the same as the architecture described above, and two new layers (Burhan et al., 2018):

1. *Processing Layer:* also known as *middleware layer*, it has the responsibility to collect the data sent from the transport layer and process them by eliminating no meaning or extra information and extracting the relevant ones.
2. *Business Layer:* by acting as a manager of the whole system, it has the responsibilities to manage and control the applications, businesses and profit models of the IoT. It also determines how information can be created, stored and changed and ensure the user's privacy.

Fig. 1.1 represents the hierarchy of all the above described structures of the Internet of Things (IoT), respectively the three layer, four layer and five layer architecture (Burhan et al., 2018).

Fig. 1.1. Internet Of Things (IoT) Architectures



Source: Burhan et al., 2018

1.6 The Internet of Things (IoT): *from Smart products to Smart services*

The Internet of Things (IoT) brings the intelligence of the Internet to physical products (Hoffman & Novak, 2015) also known as *Smart Objects*. Smart objects are "*physical embodiment with communication functionality, possessing a unique identifier, some basic computing capabilities and a way to detect physical phenomena and to activate actions having an effect on physical reality"* (Hsu & Lin, 2016, p. 516). They are enhanced with computing and communication technology that enable them to join the communication framework and to interact and communicate both with people and other smart objects (Hsu & Lin, 2016) on "*an ongoing basis by sending and receiving data through the Internet that are then stored and organized in a database"* (Hoffman & Novak, 2015, p. 14). The multitude forms of communication enabled can be referred to as consumer-to-machine (C2M), in which interactions occur between customers and the devices, machine-to-machine (M2M), in which digital interactions occur between devices, machine-to-physical world (M2P), in which interactions occur between devices and the physical world, and consumer-to-consumer (C2C), in which interactions occur between customers through these devices (Hoffman & Novak, 2015). Smart objects have "sensors" that enable them to collect data from the environment surrounding them, "actuators" controlled by other entities that enable them to activate actions and "network connectivity" that enable them to be connected to each other and to the Internet in several different form, such as Wi-Fi, Bluetooth or RFID (Mani & Chouk, 2017). Each object has a unique digital identity (Aggarwal et al., 2012) which make them machine readable, traceable and addressable through information sensing device and on the Internet (Madakam et al., 2015, Patel et al., 2016). Such digital identity is embedded/attached to each object by the Radio Frequency Identification (RFID) technology that uses RFID tags, each of which has a unique identification (Aggarwal et al., 2012).

They are perceived as representing a revolution of the original product (Ram, 1987) and present the following main features[8]:

1. *Connectivity:* the "thing" has to be connected to the Internet and such connection can be provided by the device itself or by another base station, which is probably collecting data and operational information that are then passed and store in a cloud. The connection of objects can be wireless, as in the case of Radio Frequency Identification (RFID) and Radio Sensor Technologies or wired, as in the case of Power Line Communication (PLC) (Chaouchi, 2010).
2. *Sensors:* important components of a device, since they can monitor, track and measure its activities and interactions and then transmit these data into a cloud. Examples of sensors may be those that can detect whether a door is open or closed, whether an individual is running or just walking etc.
3. *Processors:* all devices connected to the Internet of Things (IoT) must have a certain degree of computing power. It means that such devices need to have a processor, even if they only have to accomplish simple tasks like collect and relay data and information to the cloud.
4. *Security:* it is critical that there is a high level of security in the activities of these devices especially for what concern data transmission. Indeed, most of the information and data collected by these devices are sensitive and need a certain level of protection. An example are health related or financial data.
5. *Energy-efficiency, Quality and Reliability:* all devices must be energy efficient, must be made with the highest quality and their activities must be reliable. These features guarantee that these devices can operate in severe conditions and hard to reach places, like outer space or deep inside mines.
6. *Cost effectiveness:* devices with sensors able to collect and transmit information and data to be effective need to be widespread. Thus, they have to be cost effective and sensors need to be relatively cheap to be implemented in every object.

[8] https://www.webchoiceonline.com.au/fundamental-characteristics-that-makes-the-internet-of-things-what-it-is/ [accessed 02/03/2020]

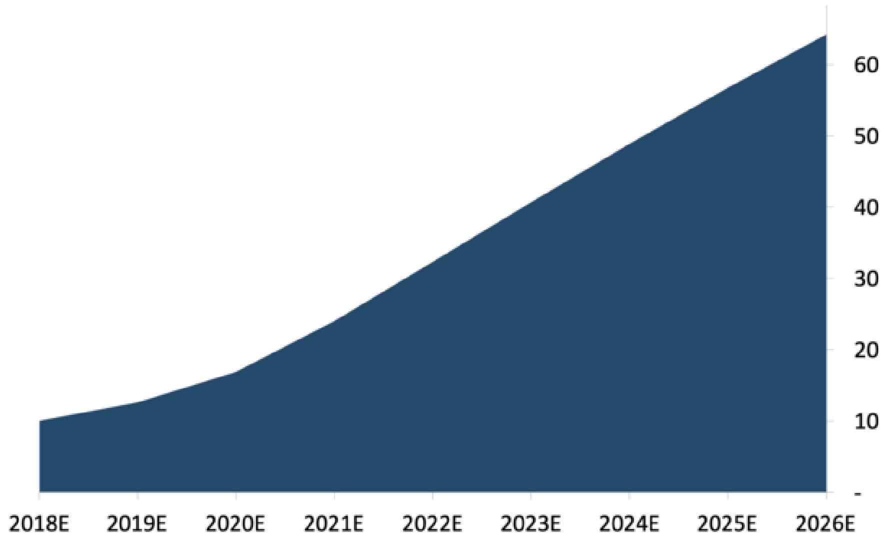
In summary, these elements permit smart objects to: (1) collect, aggregate and analyse a significant amount of data, (2) interact and communicate with each other and with humans and (3) activate actions instantaneously and autonomously (Mani & Chouk, 2018). The data collected are then aggregated and analysed to benefit companies, that can gain a better understanding of their customers and deliver more relevant and personalized offerings (Ostrom et al., 2015). The degree to which an object is considered "smart" depends on its agency, autonomy and authority capacity. Agency is the capacity to influence and be influenced by other devices (Franlink & Graesser, 1996). Autonomy is the capacity to operate autonomously and independently from other devices (Parasuraman et al., 2000) and authority is the capacity to control other devices and take own decisions (Hansen et al., 2007). These capacities are contingent upon three factors: the properties of the smart product, such as whether it has an embedded artificial intelligence and machine learning, the presence of other devices and the interactions of the smart object with other entities as part of the assemblages (Novak & Hoffman, 2019). Rijsdijk et al. (2007), instead, relate the intelligence of the object with six key dimensions: autonomy, ability to learn, reactivity, ability to cooperate, human-like interaction and personality.

New business opportunities have emerged by integrating these technological objects into the development of new services, known as *Smart Services* (Wünderlich et al., 2013, 2015). Smart Services differ from traditional services due to the following main characteristics: a connection between the physical and the digital world, a positive impact in the value creation and an increase in economic efficiency, an extension of products and services with a digital level, transformation of the product into a part of a service, change from product centred to customer centred business model, a strong dependence on data, a required high agility during the development and cross-company and cross-sectorial production (Steimel, 2016; Eurodata, 2015; Allmendinger et al., 2005; Kagermann et al. 2015).

Smart products and smart services are growing steadily with applications in different domains (Mani & Chouk, 2018). Indeed, based on the forecasts of *Business Insider Intelligence*, represented in Fig. 1.2, by 2026 there will be more than 64 billion devices connected to Internet, with consumers and companies spending around $15 trillion over them, their solutions and supporting systems.

Fig. 1.2. Total IoT Device Installation Base

(Billions, global)



Sources: Business Insider, 2019

Fig. 1.3 shows some examples of smart product and their related applications.

Fig. 1.3. Smart Product Examples

Examples of smart products	Segment	Description/ Examples of applications		
		Sensors	Actuators	Connectivity
Smartwatch (apple.com)	Wearables	Monitoring physical activity: track steps, running, calories burned, elevation and distance, detect inactivity of the body.	- Smartwatch senses when user stands and moves. - If user has been sitting for almost an hour, smartwatch reminds him to get up with notifications.	- It connects to the internet with WiFi and 3G networks. - It automatically syncs to IPhone and Mac with Bluetooth (read mails, sms, …)
Advanced Health Tracker (withings.com)	Health	- Measure heart rate and blood oxygen level with a single touch. - Analyse a night and sleep cycles.	The mobile application 'Health Mate' turns data into graphs showcasing the day-to-day progress to better understand how user habits impact their health.	It automatically syncs to smartphone all throughout the day thanks to its embedded Bluetooth Low Energy technology.
Ikettle (smarter.am)	Smart Home	- Automatic start when the user wakes up. - It senses the presence of the user;	It sends invitations on Facebook and twitter.	It can connect to the home WiFi network.
Driver tracking tool *'Pay how you drive'* (Youdrive.fr)	Mobility	GPS data collected from the vehicle, including speed and time-of-day information, historic riskiness of the road.	Information on the score of driving is displayed on the car dashboard	The data is sent to the server of the company via cellphone or RF technology.

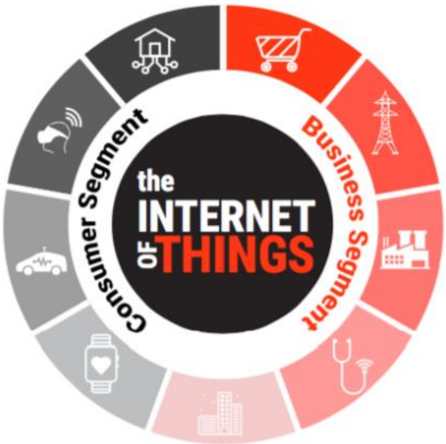
Source: Mani Z., Chouk I., 2017

More detailed applications are described in the following Section 1.7.

1.7 The Internet of Things (IoT): *Applications*

Applications and opportunities to use the Internet of Thing are numerous and diverse (Patel et al., 2016). They can be extended to almost every aspects of every-day life of individuals, companies and society as a whole, improving the quality of lives in many different sectors and environments (Atzori et al., 2010, Rose et al., 2015, Patel et al., 2016). Literature has divided the IoT applications into two macro-categories: the first one relating to the human sphere (*consumer segment*) and the second one relating to the business world (*business segment*), as it is represented in Fig. 1.4 (GrowthEnabler, 2017).

Fig. 1.4. The two spheres of the IoT Applications



Source: GrowthEnabler, 2017

The main applications belonging to the first segment are: connected homes, wearables, connected cars and personal health. With regard to the business segment, it is important to mention the following innovative solutions: retail, smart utilities and energy, industrial IoT (IIoT), healthcare and smart city (GrowthEnabler, 2017). All of the application mentioned are described in more details in the second classification introduced below.

Literature classifies the environments in which these advanced smart solutions can be applied into the following four domains (Atzori L. et al., 2010):

- *Transportation and industrial IoT domain (IIoT)*
- *Healthcare domain*
- *Smart environment domain*
- *Personal and social domain*

The IoT application domains are very diverse and serve different users. The latter are classified in three different categories: (1) Individual citizens, (2) Community of citizen (citizens of a city, a region, country, or society as a whole), (3) The enterprises. Each of these groups has its own different driving needs in the usage of the IoT applications (Patel et al., 2016).

1.7.1 *Transportation and industrial IoT domain*

In the field of transportation, cars, trains and busses as well as roads could be equipped with sensors, actuators and processing power incorporated, which, for example, can provide critical information to the driver and/or passengers in order to guarantee a better navigation and safety, to better monitor traffic patterns for planning purposes, to provide information to drivers about the jam and incidents, to avoid collision and monitor the transportation of hazardous materials. Another important application in the field of transportation is mobile ticketing. Through posters or panels, equipped with an NFC tag, a visual marker and a numeric identifier, the user can get information about several options of transportation services (description, costs and schedule) by either hovering his mobile phone over the NFC tag, or pointing the mobile phone to the visual markers. Then the mobile phone enable the user to buy the related tickets. The Internet of Things (IoT) also enable to monitor the conservation status, such as temperature, humidity, shock, of perishable goods (fruits, meat, fresh-cut produce and dairy products) during the transportation in order to guarantee high quality levels for distribution purposes (Atzori et al., 2010). Goldman Sachs, in its report "The Internet of Things: The Next Mega-Trend" (2014) has tried to picture the revolution led by the Internet Of Things (IoT) within the industrial domain that has gave birth to the term "Industrial Internet of Things (IIoT)":

"The global industrial sector is poised to undergo a fundamental structural change akin to the industrial revolution as we usher in the Internet of Things. Equipment is becoming more digitized and more connected, establishing networks between machines, humans, and the Internet, leading to the creation of new ecosystems that enable higher productivity, better energy efficiency, and higher profitability. While we are still in the nascent stages of adoption, we believe the Internet of Things opportunity for Industrials could amount to $2 trillion by 2020. The Internet of Things has the potential to impact everything from new product opportunities, to shop floor optimization, to factory worker efficiency gains that will power top-line and bottom-line gains." [9]

All of these changes will create a new balance that will increase profitability, productivity and efficiency, an optimization of production and processes and a reduction of failures. Moreover, the Industrial IoT (IIoT) drives business bottom line by lowering operating costs and risks, increasing productivity and expanding to develop new product offerings and market segments (GrowthEnabler,

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[9] Sachs, G. (2014). *The Internet of Things: The next mega-trend.* Goldman Sachs. Available at: https://www.goldmansachs.com/insights/pages/internet-of-things/.

2017). Within the industrial domain, even the field of logistics benefits, both at the company and customer level, from the application of these advanced technologies. Companies can monitor in real time all steps in the supply chain, from raw material sourcing and storage, to distribution and after-sales processes, and obtain timely and accurate product information to respond promptly to market needs. It also has implications on the offline retail context. From the consumer's point of view, real-time warehouse management can help shop assistants better assist consumers by informing them about the precise availability of a product. Finally, through interactive panels, the user could receive detailed information and, for example, buy a specific product or service simply by pointing their mobile device (Atzori et al., 2010). Customers can be reached by proximity-based advertising and can use intelligent payment solutions (GrowthEnabler, 2017).

1.7.2 *Healthcare domain*

The Internet of Things (IoT) applications in the domain of healthcare are multiple as well as the benefits they provide. These applications are grouped according to their purpose, that may be: tracking of people and objects, authentication and identification of people, automatic data collection and sensing (Atzori et al., 2010). For what concern tracking, it enables to monitor and identify the real-time position of a person or object in motion. It includes the monitoring of patient-flow and the tracking of people access to specific areas to improve the workflow in hospitals. Tracking of objects is applied to monitor the inventory, such as maintenance, availability and use, and to prevent that materials are left in during surgery (Atzori et al., 2010). Identification and authentication in relation to people is used to reduce harmful incidents to patients (wrong drug, dose, time and procedure), to maintain a complete and current medical record, to identify infants in hospitals, to grant access to staff and so on. In relation to objects, identification and authentication is mostly used to avoid losses or thefts of instruments and to meet the security requirements of procedures (Atzori et al., 2010). Authomatic data collection and tracking are mostly applied to reduce the time needed to process form, to enable process automation (including data entry and collection errors), automated care and procedure auditing and medical inventory management (Atzori et al., 2010). Lastly, sensing devices provide real-time information on patient health indicators enabling to monitor patient conditions. Other applications include different telemedicine solutions, the monitoring of patient’s compliance with medication regiment prescriptions and of the patient well-being. Also, the development of wireless access-based remote monitoring systems enables to access the patient everywhere. (Atzori et al., 2010).

1.7.3 *Smart environments domain*

One of the most interesting areas of applicability of the Internet of Things (IoT) is the smart environment, i.e. the transformation of environments into intelligent systems composed of autonomous and interconnected devices. Objects equipped with sensors and actuators distributed at home or office can make life more comfortable from several points of view: the heating system could be adapted to our preferences or to the outdoor climate conditions; the lighting could automatically adjust according to our needs or time of day; incidents could be avoided with appropriate alarm systems; the waste of electricity could be avoided by turning off the device when not in use (Atzori et al., 2010). The Internet Of Things (IoT) principles applied to urban innovation leads to the development of an intelligent city, also known as *Smart City*. Taking advantage of the many opportunities offered by new communication technologies, it is possible to develop urban planning strategies with the aim of connecting the city's material infrastructure with the intellectual and social human capital of its citizens in order to improve the quality of life.[10] As seen in the previous section, transport activities can be facilitated by the application of IoT technologies. Specifically, in the context of the smart city, these solutions are used for public transports. Gyms and museums are two representative examples in which the application of the IoT technologies can create smart leisure environments within a city. For instance, expositions in the museums can have different climate conditions as to evoke the historical periods of the related exposition. The structure would take into account external and internal conditions to offer a realistic experience to visitors. In the gym, it would be possible to monitor health parameters during the training session and check the reported values to see if the trainee has performed the exercise properly. It can be achieved by inserting the exercise profile into the training machine, which recognise the identity of the trainee and then collect information about the work out session (Atzori et al., 2010).

Other examples of IoT applications in the Smart City domain are (Vermesan et al., 2014):

- *Smart Lighting*: streets light adapts to weather, time of the day and external conditions.
- *Smart Structural Health:* vibrations and material conditions in building, monuments and bridges are monitored on a continuous base.
- *Smart Tourism:* tourists could be provided with useful information regarding museums, art galleries, libraries, touristic attractions, shops, taxis, buses etc. of the city they are visiting.

[10] *Smart city. Lessico del XXI Secolo* (2013). Enciclopedia Treccani online. Available at: http://www.treccani.it/enciclopedia/smart-city_%28Lessico-del-XXI-Secolo%29/ [accessed 05/03/2020].

- *Smart Irrigation of public spaces:* parks could be provided with monitoring sensors in the ground enabling irrigation and correct maintenance.
- *Safe City:* cities could be provided with fire control, public announcement systems and digital video monitoring.
- *Waste Management:* it could be possible to detect the rubbish levels in containers to optimize the trash collection.
- *Smart Parking:* citizens could be provided with information about the parking spaces availability in order to help them find and reserve the closest available spaces.

Smart Home is another important application of the IoT technology (GrowthEnabler, 2017). It can be defined as an integration of technologies and services to create a house with automated or remotely controlled smart components connected via Wi-Fi to enable a harmonic interaction among them in order to create an environment in which activities can be monitored and controlled with or without the human intervention (Kadam et al., 2015). Examples are smoke detectors, light bulbs, entertainment system, security systems, automated thermostat, a smart lighting system, smart blinds and smart appliances (a refrigerator, an oven, a dishwasher) that you can monitor and control remotely turning them off and on just by using a mobile app.[11] The advantages that are gained from the use of these devices consist in the improvement of the owner's well-being, comfort, convenience and safety as well as a considerable saving in terms of costs related to the management of resources and energy consumption (Kadam et al., 2015). A recent introduction in the smart home environment is represented by the Smart Home Assistants, also known as Virtual Assistant. It is a software installed into a device, such as a smart speaker or a smart phone. These devices are equipped with Artificial Intelligence. The user by interacting with them can control other smart home appliances, asking them to perform different tasks or services. Examples include Alexa by Amazon, Siri by Apple and Google Assistant by Google. The main feature of these voice assistants is that the more you use them, the better the interpretation of commands ordered by the owner, in line with machine learning principles.[12]

1.7.4 *Personal and social domain*

The applications belonging to this domain are all those that enable the interaction between people in order to build social relationships. Social network is one of the major applications. These platforms enable users to automatically update personal information and share them on social portals. RFID sensors located on every device may automatically share user-generated information, such as photos,

[11] https://techterms.com/definition/smart_home [accessed 10/03/2020].
[12] https://www.realhomes.com/advice/smart-assistants [accessed 10/03/2020].

videos or consumption habits, on the network to generate useful feedback for other users. The data collected by the devices used could be stored and classified to create a kind of digital diary. Such diary would let users identify historical trends and patterns of behaviours over time, in order to enable them to better plan and manage their life (Atzori et al., 2010). Wearables are another application of the IoT technology. These are electronic devices that can be worn, tattooed, implanted in the human's body or applied on clothes. Like other smart objects they have a microprocessor and are connected to the Internet. They can collect, send and receive data and information. These devices can monitor and track the user's activities and provide statistics about the owner's daily routine as well as suggestions to improve the quality of his life. Examples includes smartwatches, Bluetooth headsets, smart glasses, fitness trackers and so on. Recently, the gaming industry has introduced other wearables such as virtual and augmented reality headsets and glasses.[13] The most popular among wearable devices is certainly the smartwatch, an intelligent watch that through Wi-Fi or Bluetooth technology connects with the owner's smartphone, with which it communicates constantly enabling the user send and receive text messages, receive and answer calls and much more without using the smartphone. Furthermore, these devices can monitor the heart rate, track your activity and provide reminders. Therefore, it is clear that their functioning depends on the connection to a smartphone. The reason is that the smartphone acts as an intermediary of the data sent and received by the smartwatch. [14] Finally, by equipping any personal objects with sensors, it could be possible to prevent thefts or losses simply by indicating to the user their position or any unauthorized movement from a restricted area (Atzori et al., 2010).

1.8 The Internet of Things (IoT): *market overview*

1.8.1 *The IoT market drivers and related phenomena*

The phenomenon of the Internet of Things (IoT) has grown fast in the latest years, even if the idea of connecting objects to each other and to the Internet is not new. The reason for this rapid growth is the convergence of various advanced technologies with new emerging computing and connectivity trends. Both phenomena are enabling more and smaller devices to interconnect cheaply and easily. The main drivers of this Internet revolution are (Rose et al., 2015):

1. *Ubiquitous connectivity:* nowadays, through the use of low-cost, high-speed and pervasive network connectivity based on licensed or unlicensed wireless services and technology, almost everything can be "connectable".

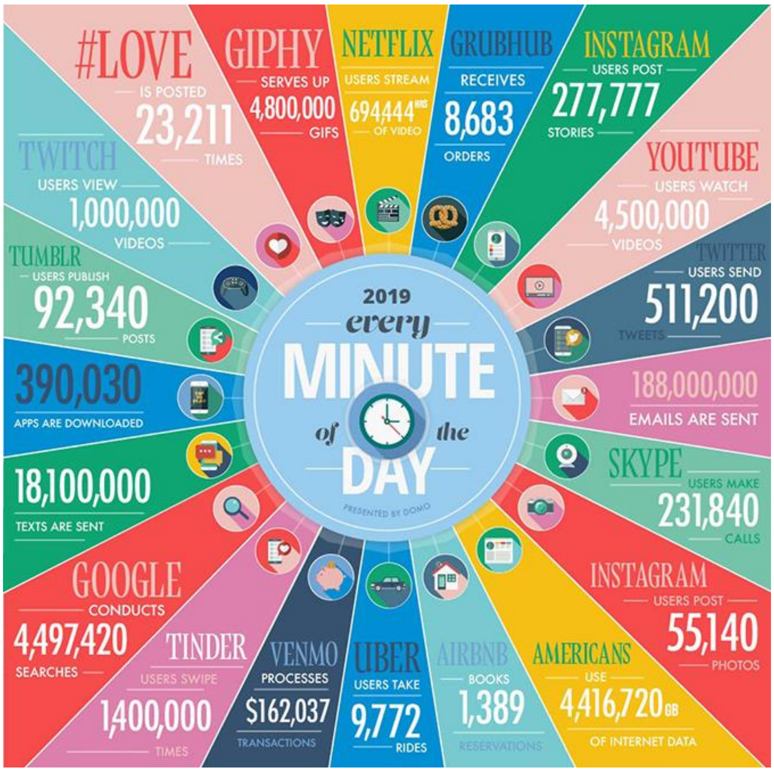
[13] *Investopedia.com:* https://www.investopedia.com/terms/w/wearable-technology.asp [accessed 10/03/2020].
[14] https://techterms.com/definition/smartwatch [accessed 06/03/2020].

2. *Widespread adoption of IP-based networking:* it has become the dominant global standard for networking. It provides tools and platform of software to incorporate into multiple and different devices easily at a low cost.
3. *Computing Economics:* thank to the huge amount of investment in research, development and manufacturing, it is possible to deliver greater computing power at a lower price and power consumption.
4. *Miniaturization:* as manufacturing progresses, technological and communication components are produced in smaller size as they be integrated into very small objects. Together with the development in computing economics, they have favoured the creation of small and inexpensive sensor devices, which drive many IoT applications.
5. *Advances in Data Analytics:* the advances in computing power, cloud services, data storage and the introduction of new algorisms enable the implementation of advanced techniques in the analysis of vast quantities of data providing new opportunities to extract knowledge and patterns.

In addition, it is important to introduce and briefly describe three important phenomena that have developed over the last decade as these have contributed significantly to the rapid growth of the Internet of Things (Iot): *Big Data*, *Machine Learning*, and *Cloud Computing*.

The incessant increase in the use of information-generating smart technologies is giving rise to the phenomenon of Big Data. There is not one single universally accepted definition for this term, although everyone recognizes its importance as well as the fact that this abstract concept do not just refers to the large volume of data collected (Chen et al., 2014). Big data, considered as the next frontier for innovation, competition and productivity by the global consulting agency McKinsey & Company in 2011, were first defined in 2010 by Apache Hadoop as "*datasets which could not be captured, managed, and processed by general computers by classic database software*. In 2011, an IDC report specifies that *Big Data technologies describe a new generation of technologies and architectures, designed to economically extract value from very large volumes of a wide variety of data, by enabling the high-velocity capture, discovery, and/or analysis"* (Gantz,& Reinsel, 2011). From this definition it is possible to identify the four main features of Big Bata which can be summarised as the "four Vs": Volume, Variety, Velocity and Veracity (Forbes, 2019). Velocity refers to data generation speed. Volume refers to the massive size of the datasets that are collected, processed and analysed. Volume and velocity are correlated: the amount of data grows exponentially every second and this trend is strongly driven by an increase of the world's Internet population and accelerated by the advances in the Internet of Things (IoT) (Forbes, 2019). The cloud software firm DOMO documents every year in a report "Data Never Sleeps" the amount of data generated every minute in ad clicks, likes, shares, transactions, streaming contents and so on. *Data Never Sleeps 7.0*, represented in Fig. 1.5, collects data related to 2019. The numbers are impressive. Every minute Google search engines processes around 5 million searches, Twitter users send 511,200 tweets, 188 millions Emails are sent, Instagram users post 55,140 photos, YouTube users watch almost 5 million videos and so much more. However, digital data are not just created by user's activities on social media and communication channels (text messages, emails and so on). Interesting statistics are also generated by businesses and service providers, like the forecast requests on The Weather Channel, trips taken by Uber drivers, the number of new page edits to Wikipedia, and by the connected smart objects, considered as one of the most important source of digital data (Forbes, 2018). Each of this activity generates data at a rapid pace. Based on the IDC predictions the total amount of data created on digital platform will rise to 163 zettabytes by 2025, mainly driven by the development and dissemination of smart devices (Forbes, 2019).

Fig. 1.5. "Data Never Sleeps 7.0" Report



Source: DOMO report, Data Never Sleep 7.0, 2019

Variety of Big Data, instead, relates to the great multiplicity of data formats, generally structured, semi structured and unstructured, which depends from the source that generates them. Different formats require different techniques and algorithms to be processed and analysed. Lastly, the veracity feature refers to the quality of the data collected. The higher the veracity the more valuable data are contained into the dataset. On the other hand, the lower the veracity the more the meaningless data or "noise" have been collected.[15]

Cloud Computing is for sure one of the technologies that has revolutionized the data management industry. Information can be processed on intelligent terminals. However, if they have limited computational power or storage capacity, then this task can be accomplished by a cloud computing platform (Min, 2013) It is a range of tools and applications that, through the Internet, enable data to be collected and processed using hardware and software resources distributed across the network (Kiteblue, 2018). These resources include data storage, servers, databases, networking, and software. Data are stored on remote cloud-based database, which can be accessed anytime and anywhere as long as an electronic device is connected to the Internet enabling cost savings, an increased productivity, a higher speed and efficiency, a better performance and security for both individuals and companies. Therefore, cloud computing offers very flexible computing and storage capacity, overcoming the need for a physical hardware device. Examples are Google Drive and iCloud.[16]

The last phenomena correlated to the development of the IoT is Machine Learning, a branch of computer science. It is an application of Artificial Intelligence (AI), which focuses on the development of computer programs that have the ability to automatically learn from experience by observing phenomena and analysing the big volume of data collected during their activities in order to find patterns. The aim is to improve the performance of the system for a better decision making in the future with the minimum human intervention.[17] The convergence between Internet of Things (IoT) and Artificial Intelligence (AI) will lead to the development of smart objects that can learn from experience, such as the user's behaviour, and operate autonomously with a decentralized control. Therefore, these smart devices can perform their activities and take optimal decisions without being always connected to a centralized cloud to which they can connect anytime in case of need. Currently, a myriad of IoT applications take advantage of Artificial Intelligence, especially the machine learning techniques. This will offer multiple opportunities for new innovative applications and revenue streams. Examples are self-driving cars and robots.[18]

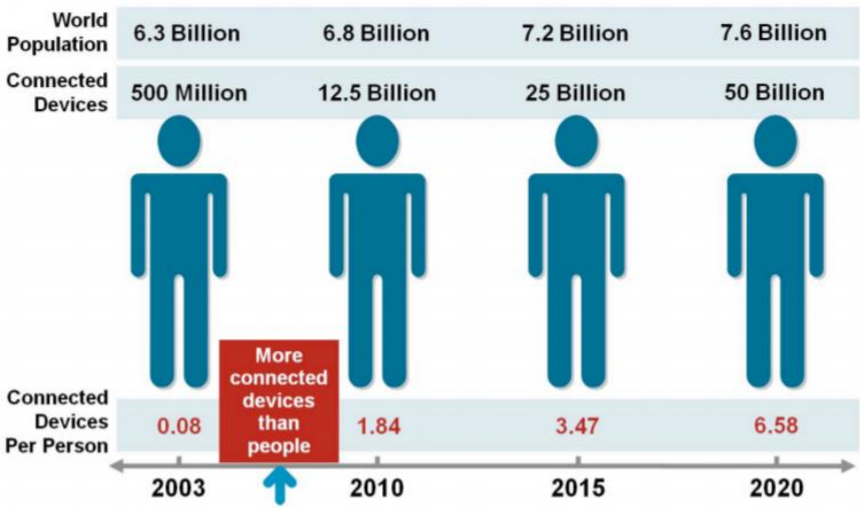
[15] BigDataFramework.com (2019). *The four characteristics of Big Data.* Available at: https://www.bigdataframework.org/four-vs-of-big-data/ [20/03/2020].
[16] *Investopedia.com:* https://www.investopedia.com/terms/c/cloud-computing.asp [21/03/2020].
[17] Expert System (2017). *What is Machine Learning? A definition*. Available at: https://expertsystem.com/machine-learning-definition/ [accessed 21/03/2020].
[18] https://nextgenexecsearch.com/smart-objects/ [22/03/2020].

1.8.2 *The IoT market volume and value*

After having defined the concept of the Internet of Things (IoT), having identified its main features, enabling technologies, architectures, multiple applications, drivers and related phenomena, it is important to quantify the impact it has on the market in terms of volume and value.

The Cisco Internet Business Solution Group (IBSG, 2011, p.2) defines the Internet of Things (IoT) as "*the point in time when more things or objects were connected to the internet than people*." Based on Cisco's market research this phenomenon did not exist in 2003 since there were approximately 6.3 billion people on planet and only 500 million connected devices; there were less than one device per person (0.8) and the main reason was that the smartphones had just been introduced into the market. Fig. 1.6 shows that, only in 2010, the number of connected devices were more than one per person, 1.84 to be exact. That year, the human population reached 6.8 billion and the number of devices connected to the Internet grew exponentially to 12.5 billion driven by the rapid development of smartphones and tablets. Thus, based on Cisco IBSG (2011) definition and estimates the IoT phenomenon was "born" around 2008 and 2009. Cisco IBSG (2011) has also predicted that the number of connected devices in 2020 will be 50 billion and the world population will reach 7.6 billion. It means that there will be 6.58 devices per person.

Fig. 1.6. Cisco IBSG Estimates

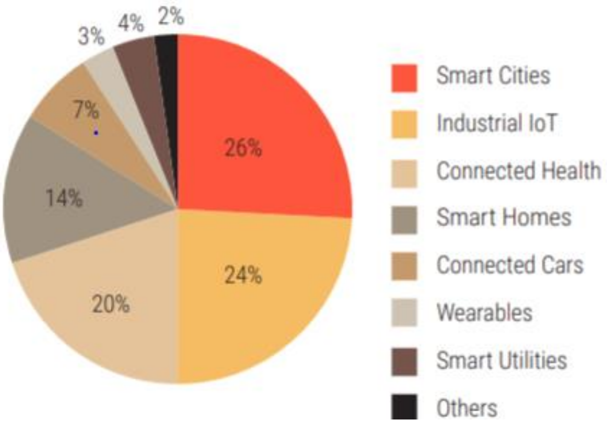


Source: Cisco Internet Business Solution Group (IBSG), 2011

Based on GrowthEnabler Analysis (2017), since 2015 the number of connected devices has grown at a CARG of 16% and therefore it will reach 27 billion by 2025. The global IoT market share will be mainly captured by USA (22%), China (19%) and Japan (6%). Moreover, based on estimates, the sub-sectors will divide the global IoT market share as follow: Smart Cities (26%), Industrial IoT

(24%), Connected Health (20%), Smart Homes (14%), Connected Cars (7%), Smart Utilities (4%) and Wearables (3%). See Fig. 1.7. Thus, it is evident that Smart city, Connected Health and Smart Homes will dominate the market (GrowthEnabler, 2017).

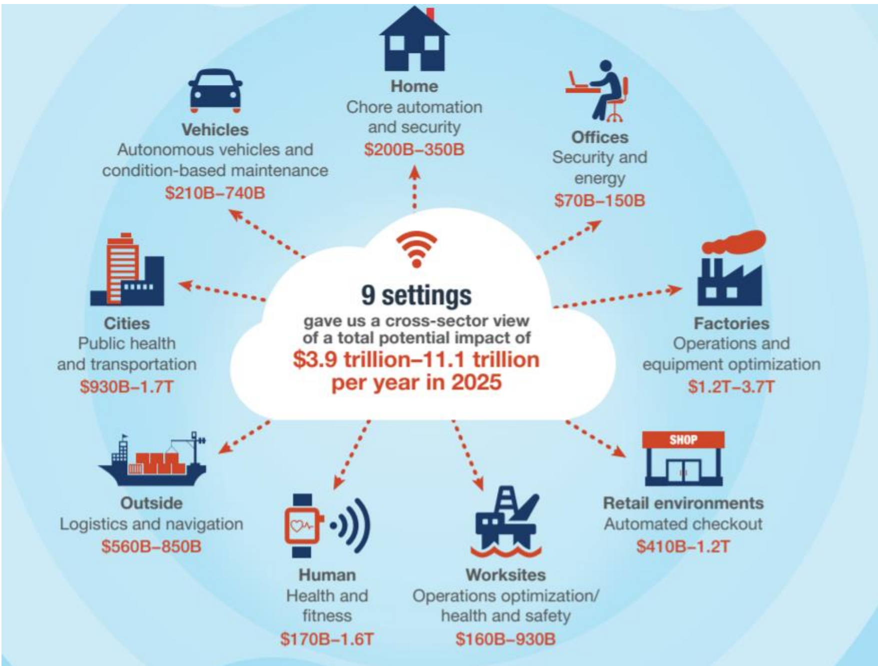
Fig. 1.7. Global IoT Market Share per sub-sector



Source: GrowthEnabler, 2017

In regard with market value, based on McKinsey market research (2015), represented in Fig. 1.8, the potential market value generated by nine application settings of the IoT technology could be worth between 3.9 and 11.1 trillion dollars per year in 2025. (McKinsey Global Institute, 2015) The three-setting generating the highest market value in dollars are Industrial IoT (IIoT), Smart City and Connected Health (in line with Cisco's market research) (McKinsey Global Institute, 2015).

Fig. 1.8. IoT Market Value



Source: McKinsey Global Institute, 2015

Chapter II

Theoretical framework:
A literature review on customer resistance to innovations in the Internet of Things (IoT) Era

Smart objects can be considered as building blocks of the Internet of Things (IoT). They are physical objects with sensors and actuators that, through a network connectivity, can interact with other entities (things or humans), detect phenomena around them and execute actions having effects on reality (Hsu & Lin, 2016). Smart objects can be applied in the development of IoT-based services, known as smart services (Mani & Chouk, 2017; Porter & Heppelmann, 2015). Their three main features are intelligence, ubiquity, autonomy and connectivity. Intelligence is the ability to learn, adapt and react to different situations similarly to humans. Ubiquity refers to the fact that such devices are now very common and present everywhere. Autonomy is the ability to activate actions independently without the human intervention. Lastly, connectivity refers to the fact that they are connected to the Internet and to each other and this enables them to communicate and exchange data (Porter & Heppelmann, 2014). Smart products are radical and revolutionary transformation of the original product (Ram, 1987) and smart services represents a new way of benefiting from traditional services; they are both perceived by customers as something different and new. Therefore, given the main characteristics of smart objects and smart services and the intense impact they have on customers' live, they can be considered not only as simple innovations but even as disruptive innovations (Christensen, 1997).

It is widely demonstrated in academic literature that, contrary to what Rogers (2003) argued, the process of diffusion of an innovation and its success do not have to be taken for granted. As a matter of fact, the slow pace of customer adoption of new technologies is one of the biggest issues in the Internet of Things (IoT) industry. Most of the new smart products and services, once launched on the market, do not become commercially successful. Therefore, understanding which are the factors that cause both customers' resistance and adoption in the specific IoT context is critical to develop and market new products and services. These insights could help firms reduce innovation failure (Ram & Sheth, 1989), could enable them to change the attributes of new products to reduce negative reactions (Ram, 1987) and increase the adoption rate (Talke & Heidenreich, 2014). Furthermore, in a context in which customers have a huge power, they can express their resistance by taking actions against the company, spreading negative word-of-mouth, boycotting or even rejecting the innovations. All of this has significant negative consequences for businesses. Consequently, although it is important to examine the factors that cause customer adoption, identifying and investigating the barriers that lead to innovation resistance represents a greater opportunity (Wiedmann et al., 2011).

This chapter is structured as follow. Section 2.1 provides a general overview of the concept of innovation and the customer adoption of innovation process, illustrated through Rogers' Diffusion of Innovation model (1995). It closes with an illustration of the main factors identified in literature that lead consumers to adopt a new product or service. However, a greater consideration is given to customer resistance to innovation. Section 2.2 introduces the theoretical fundaments to comprehend this concept by reviewing the most relevant academic contributions in this field. The discussion continues in section 2.3 by describing the major models developed over the past years to further investigate customer resistance to innovations and its determinants. The main theoretical models in the existing literature I have chosen to examine are the *Model of Innovation Resistance* (Ram, 1987), the *Consumer Resistance to Innovations Model* (Ram & Sheth, 1989) and the *Customer Resistance to, and Acceptance of, Innovation Model* (Bagozzi & Lee, 1991). Since the focus of this study is the Internet of Things (IoT), more focus is given to Ram and Sheth's (1989) model, its extensions, applications and related findings that are particularly relevant to better comprehend customer barriers towards smart products and smart services. Therefore, in section 2.4 relevant studies on innovation resistance in the Internet of Things context are discussed. A closer attention is given to Mani and Chouk (2018)'s model, since they adjusted the Customer Resistance to Innovations model (Ram & Sheth, 1989) to the digital age by adding new categories of adoption barriers. The chapter ends with an overview of literature evidences of the impact of demographic variables on customer resistance to innovations.

2.1 Customer Adoption of Innovation

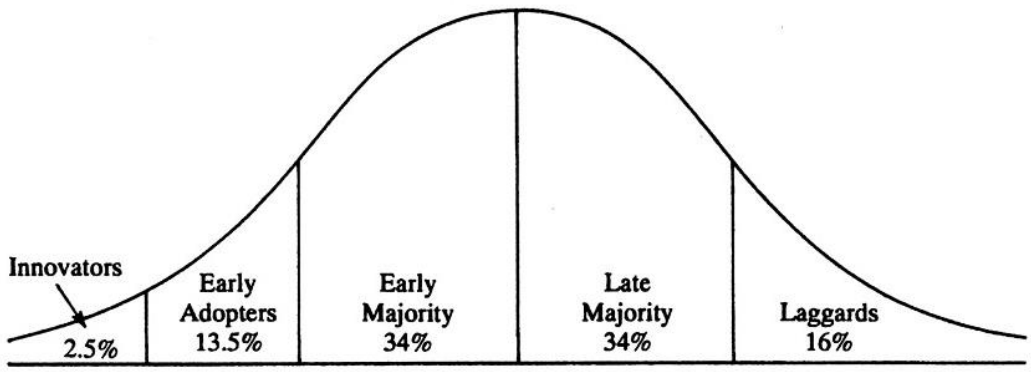
Rogers (1995, p. 11) defined innovation as "*an idea, practice or object that is perceived as new by an individual or other unit of adoption.*" Therefore, the basic assumption for adoption to occur is that the new product, idea, service or behaviour is perceived as new or innovative. An innovation may have been invented a long time ago, but if individuals perceive it as new, then it may still be an innovation for them. The newness perception can derive from changes in just one product attribute or from a radical change in the product or service concept. Innovations can be classified as continuous and discontinuous. Continuous innovation results from improvements of the existing product or service attributes or from the introduction of new attributes. Discontinuous innovation derives from the creation of an entirely new product or service (Lee, 1994). Even if Rogers (2003) has assumed that all innovations are good and should be adopted by everyone since they are improvements of existing products or service substitutes (Ram, 1987), a large majority of them, once launched on the market, commercially fail (Gourville, 2006). In this context, marketing literature has identified two research paradigm that explain customer response to innovation (Laukkanen, 2016): *innovation adoption* and *innovation resistance.*

Adoption can be defined as "*the acceptance and continued use of a product, service or idea"* (Sathye, 1999, p. 325). The theoretical foundations to explain user innovation adoption and, thus, how it spreads in the market were provided by Rogers. In 1995, thanks to the development of the *Diffusion of Innovation Theory,* he was recognized as the father of social science as well as the pioneer of innovation diffusion research. This model has been used as a framework in multiple fields and in conjunction with other theories. Rogers (1995) defined innovation diffusion as "*the process by which an innovation is communicated through certain channels over time among the members of a social system* (p. 5)". He (1995) argued that the innovation-decision process, defined as "*an information-seeking and information-processing activity, where an individual is motivated to reduce uncertainty about the advantages and disadvantages of an innovation"* (p. 172), goes through five stages:

1. *Knowledge*: the individual becomes aware of an innovation but lacks complete information about it.
2. *Persuasion*: the individual collects information and develops a positive or negative attitude toward the innovation.
3. *Decision*: the individual engages in a process that will lead to an adoption or rejection choice of the innovation.
4. *Implementation*: the individual adopts the innovation and makes full use of it.
5. *Confirmation*: the individual makes post-adoption evaluation of the innovation.

Therefore, for the process of innovation adoption to begin, it is necessary that the individual becomes aware of the new product or service (Sathye, 1999). In addition, the author suggested that the adoption process does not involve all the social system simultaneously: some people adopt the innovation earlier than others do. Rogers (1995) has defined the social system as a set of interrelated *"units engaged in joint problem solving to accomplish a common goal*" (p. 23). Every social system has a specific structure, defined as "*the patterned arrangements of the units in a system"* (p.24) that strongly influences the diffusion of innovations. Within a social system, innovation adopters can be grouped in five categories based on their different level of resistance to innovations (personal innovativeness), which has an impact on the timing of adoption (Johnson et al., 2018). Innovativeness is defined as "*the degree to which an individual or other unit of adoption is relatively earlier in* *adopting new ideas than other members of a system"* (Rogers, 1995, p. 22). Therefore, members in each category are similar on this characteristic. The five categories of adopters are: innovators, early adopters, early majority, late majority and laggards. *Innovators* are generally well-educated and search for information from multiple sources. Since they are not risk averse, they are the first adopting a new product or trying a new service. *Early adopters* are opinion leaders; they are comfortable with adopting innovations since they are aware that a change is essential. The *early majority* are willing to adopt the innovation before the average person; however, they need to see evidence that it works, and it is worth their money. On the other side of the adoption spectrum, the *late majority* and *laggard* will be the last adopting the innovation. They are skeptical towards new technologies; therefore, they wait for it to be well established and that the largest majority has adopted it. In particular, laggards are conservative and strongly attached to traditions. Time dimension also plays an important role in this model, since it is embedded in the diffusion process, the adopter categorization and the rate of adoption. Fig. 2.1 portrays the Diffusion of Innovation model as an s-shaped curve.

Fig. 2.1. Innovation Adoption Curve



Source*:* Rogers, 1995

2.1.1 Factors of adoption

According to the Diffusion of Innovation theory (Rogers, 1995), there are five main adoption factors (or innovation characteristics). Customers 'perception of each of them with regard to a specific innovation directly impacts on their adoption decision and this determinates the rate of adoption, defined as "*the relative speed with which an innovation is adopted by members of a social system"* (p. 221). The actual impact of individual's perception of these five innovation characteristics on adoption have been widely demonstrated across several types of innovation, ranging from ecological water saving devices (Schwarz & Ernst, 2008), online grocery shopping (Langerak & Verhoef, 2001) and visual customer integration (Bartl et al., 2012). The adoption factors are:

1. *Relative advantage:* the extent to which the innovation is better than what it substitutes. Rogers (1995) suggests that an innovation will be more easily adopted when it provides clear and unambiguous advantages. Prior research notes that if an individual does not perceive a higher relative advantage in using the innovation, it will be rejected (Greenhalgh et al., 2004).
2. *Compatibility*: the extent to which the innovation is consistent with the potential adopters' values, experiences and needs. Current research indicates that the higher the innovation compatibility, the higher the likelihood that it will be adopted (Greenhalgh et al., 2004).
3. *Complexity*: the degree to which an innovation is perceived as difficult to understand and use. Evidence suggests that individuals who feel confident with the functioning of an innovation are more likely to adopt it, whereas individuals who have difficulties in understanding it will be more reluctant (Greenhalgh et al., 2004). Furthermore, Rogers (1995) proposed that every innovation can be placed on a complexity-simplicity continuum.
4. *Trialability*: the extent to which the innovation can be tested before adoption. Since adopting an innovation requires many resources, in terms of money and time, the possibility of trial before purchasing reduces the level of uncertainty and risks and makes the individual more confident. Therefore, the likelihood of adoption is higher (Rogers, 1995).
5. *Observability:* the extent to which the innovation provides tangible results and benefits. In case of observable positive outcomes from the use of the innovation, it will be more easily adopted by others (Rogers, 1995).

In 1986, Davis introduced the *Technology Acceptance Model (TAM)* as an adaptation of Fishbein and Azjen (1975)'s *Theory of Reasoned Action (TRA)*. It is one of the most used models to explain customer acceptance of technological innovations, specifically with regard to information system technologies. These models aim at investigating how individuals' perception of the innovation characteristics contributes to the formation of negative or positive attitudes and how these attitudes ultimately affect the adoption or rejection decisions. In the TAM, Davis (1989) considered two new adoption factors that influence potential adopters' attitudes, intentions and computer usage behaviour. The actual effect of customers'perception of these two factors has been demonstrated across a wide range of technological innovations (Lu et al., 2009; Wu & Wang, 2005). They are:

6. *Perceived usefulness:* the degree to which a person believes that the use of a particular system could enhance the job performance. When a technological innovation is high in perceived usefulness, the individual will believe in the existence of a positive relationship between the use and the performance results (David, 1986).

7. *Perceived ease of use:* the degree to which a person believes that using a particular system would be free of effort. When a technological innovation is perceived as easy to use, it has a higher likelihood to be adopted (David, 1986).

Research in innovation adoption field are predominantly built on the Diffusion of Innovation theory (Rogers, 1995) and on the two largely applied behavioural models, the so-called Technology Acceptance Model (Davis, 1989) and Theory of Reasoned Action (Fishbein & Ajzen, 1975). However, these studies have been criticized for a lack of focus on the determinants that lead to customer resistance to innovations (Garcia et al., 2007, Ram & Sheth, 1989). Indeed, most of existing literature mainly prioritize the concepts of innovation adoption and diffusion (Gatignon & Robertson, 1985). The reasons are prevalently the researchers' "pro-innovation bias" (Rogers, 1983), based on the assumption that all innovations are good since they are improvements of existing products or services, and their tendency to classify late adopters as "laggards". However, given the high failure rate of new products and services, many researchers have emphasized the need to direct studies to examine the main barriers that prevent innovation adoption (e.g. Antioco & Kleijnen, 2010; Heidenreich & Handrich, 2015; Kleijnen et al., 2009; Laukkanen, 2016; Ram, 1989; Ram & Sheth, 1989).

2.2 Customer Resistance to Innovation

A high failure rates of new products should not be surprising. The adoption of every innovations implies a certain degree of change. However, not all changes are desirable, necessary or useful (Stiles & Robinson, 1973). As a consequence, customer resistance to innovation can be seen as a particular form of resistance to change (Ram, 1987). Resistance to change is defined as "*any conduct that serves to maintain the status quo in the face of pressure to alter the status quo* and *is associated with the degree to which individuals feel themselves threatened by change*" (Ram, 1987, p. 208). Several psychology theories (e.g. Newcomb, 1953; Osgood & Tannenbaum. 1955; Heider, 1958) suggest that individuals have a tendency to maintain a psychological equilibrium by resisting any potential imposed change. As a consequence, resistance to change can be seen as a normal customer reaction, even with regard to innovations. Indeed, it is not the innovation per se that people resist, but the changes it brings (Ellen et al. 1991, Schein, 1985).

Over the past years, multiple definitions of innovation resistance have been provided. Roux (2007) defined it as a situational attitude manifested through opposition to a situation perceived as dissonant. Ram and Sheth (1989) defined it as "*the resistance offered by consumers to an innovation, either because it poses potential changes from a satisfactory status quo or because it conflicts with their belief structure"* (p. 6). Resistance can be directed against a new product (Ram, 1989), a new service based on technological innovation (Kuisma et al. 2007) or a new market (Close & Zinkhan, 2007). It is considered as an intent or behaviour by some authors (Kleijnen et al., 2009), as an attitude (Ellen et al., 1991) or as a combination of attitude and behaviour by others (Ram & Sheth, 1989). The basic assumption for innovation resistance to be triggered off is that the individual perceives the newness in the product or service; otherwise, the lack of adoption would be caused by a simple failure of the stimulation of the newness perception (Rogers, 1995). Resistance plays a critical role in determining the commercial success or failure of any innovation, since it can delay or completely obstacle the adoption. For this reason, it has been considered as one of the major reasons for market failure of new products or services (Ram & Sheth, 1989).

Resistance can manifest itself in three different ways (Kleijnen et al., 2009; Szmigin & Foxall, 1998):

1. *Rejection*: it is a strong disinclination to accept the innovation and can derive from the negative outcome of a consumer active evaluation (Rogers, 2003), from a skepticism toward novelty (Lee & Clark, 1996) or from an innate conservatism that make individuals adverse to alter the status quo (Hirschheim & Newman, 1988).
2. *Postponement*: customers accept the innovation but may decide not adopt it in that point in time, because, for example, the circumstances are not suitable. Consequently, they decide to postpone the adoption. In this case, customer decision toward the innovation is not final, it is just delayed. Greenlead and Lehmann (1995) introduced the concept of “delay” as a form of customer resistance. They may wait for the innovation to develop over time or for it to be well established in the market. Adoption occurs only after the individual has overcome an initial resistance (Ram, 1987).
3. *Opposition*: consumers may consider the innovation a threat and act to resist adoption, for example by spreading negative word-of-mouth. This is a kind of “active rebellion”, in which customers actively engage in strategies to prevent the innovation’s diffusion. This behaviour was defined by Davidson and Walley (1985) as an *innovation sabotage* and it is most likely to affect the market mechanisms (Fournier, 1998).

Laukkaten (2016) combined Rogers’ (1983) diffusion model with the view of Szmigin and Foxall (1998) and argued that individuals, once they become aware of an innovation, can decide to adopt, postpone or reject it. Adopters accept rapidly the innovation, postponers delay the adoption and rejecters rebuff it. Ram and Sheth (1989) argued that innovation resistance exists on a continuum and varies in degree. Therefore, they have distinguished three forms of innovation resistance: *passive resistance*, that occurs if the individual feels reluctant to adopt the innovation, *active resistance*, that occurs if the individual postpones an adoption decision to reduce risk, and *very active resistance*, that occurs if the individual concretely acts against the innovation. Innovation resistance also varies across product classes and it is manly caused by the degree of change or discontinuity in which individual customers incur due to the characteristics of the innovation and the extent to which it enters in conflict with their established belief's structure. The higher the degree of change or conflict, the higher the resistance the innovation encounters (Ram & Sheth, 1989).

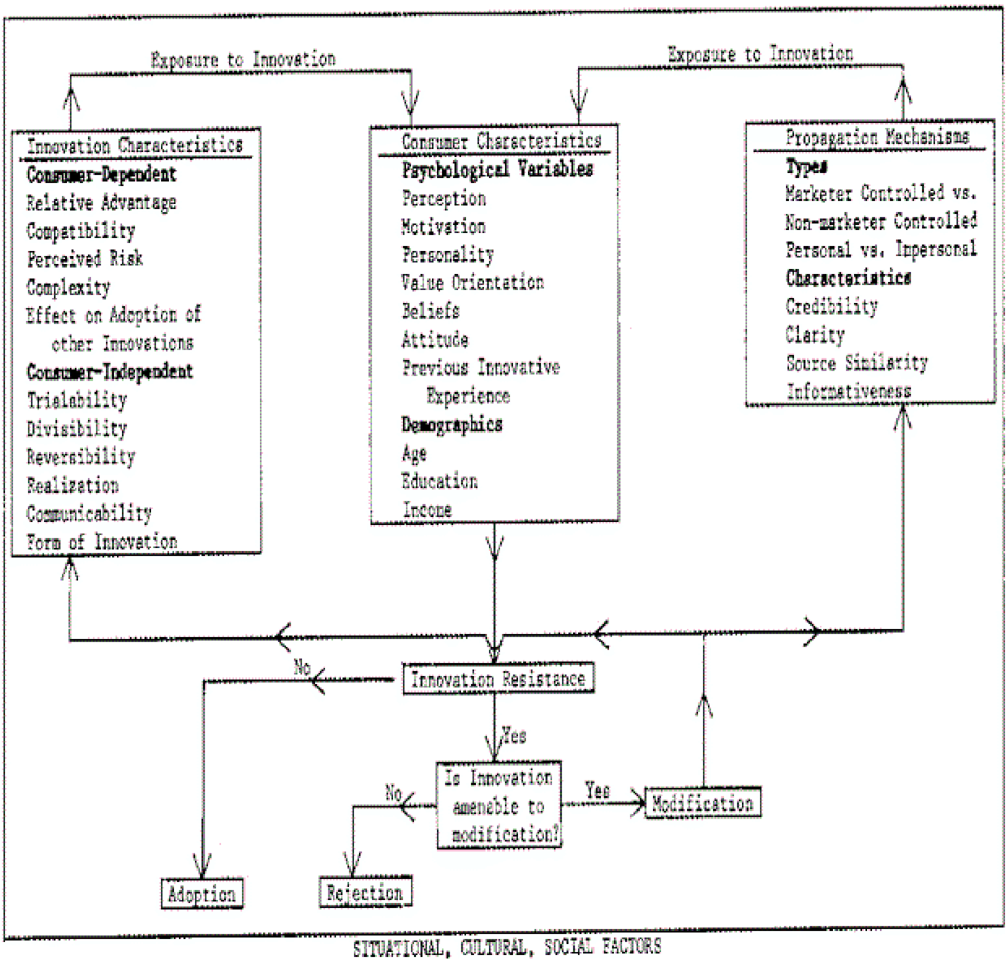
Researchers have used these theoretical foundations on the concept of innovation resistance to develop models that could explain this particular consumer response. Three of the major models identified in the literature on resistance are discussed in the following sections.

2.3 Customer Resistance to Innovation: *Theoretical models*

2.3.1 *Model of Innovation Resistance (Ram, 1987)*

In 1987, Ram introduced the Model of Innovation Resistance, based on the assumption that customer resistance is caused by three categories of determinants: *Perceived Innovation Characteristics*, *Customer Characteristics* and *Characteristics of Propagation Mechanism*. He argued that the variation of cultural, situational and social factors has a different impact on innovation resistance. However, he decided not to focus on them and to examine in further details the effects of the three above mentioned categories of determinants. Fig. 2.2 represents the Model of Innovation Resistance (Ram, 1897).

Fig. 2.2. Model of Innovation Resistance



Source: Ram, 1987

Perceived Innovation Characteristics

In this category of determinants are grouped all the main characteristics of innovation that have been previously identified in literature and that, according to Ram (1987), are relevant to explain customer resistance.

Rogers (1962) has identified five main innovation characteristics: Relative Advantage, Compatibility, Complexity, Trialability and Observability. Subsequently, Zaltman et al. (1973) suggested some other features that are particularly relevant in the context of innovation resistance: Reversibility, Realization, Amenability to Modification, and Effect on Adoption of Other Innovations. *Relative advantage* is associated to a financial or social cost saving or an economic gain that occurs when the innovation provides an improved performance at lower costs (Homans, 1961). Ram (1987) suggested that the higher the perceived relative advantage, the lower the innovation resistance. *Compatibility* refers to the extent to which the innovation is consistent with the individual’s values, beliefs, past experiences, traditions and current lifestyle (Rogers & Shoemaker, 1971). It is associated to the concept of pervasiveness, which refers to the extent to which an innovation requires behavioural changes or adjustments (Barnett, 1953). Ram (1987) suggested that the higher the perceived compatibility of an innovation, the lower the innovation resistance. *Trialability* relates to whether the customer can try the innovation before adoption and, thus, reduce the perceived risks associated. Ram (1987) suggested that if the innovation can be tried, then innovation resistance would be lower. *Observability* refers to the extent to which an innovation benefits can properly and effectively be perceived by customers through the ability of the marketer to communicate them and their tangibility. Ram (1987) suggested that the higher the observability, the lower the resistance the innovation encounters. *Complexity* refers to whether the idea behind it can be easily understood and whether it is easy to be implemented. Ram (1987) suggested that the higher the complexity of an innovation, the higher the relative customer resistance. *Reversibility* refers to whether the individual can discontinue the adoption of the innovation, temporarily or permanently. *Realization* refers to the advantages and benefits that the individuals expect to receive from the adoption. *Amenability to modifications* refers to whether the innovation can be modified over time to ensure customer satisfaction. Ram (1987) argued that the lower the reversibility, realization and amenability to modifications, the higher the innovation resistance. The *effect on adoption of other innovations* refers to the extent to which an innovation may inhibit the adoption of other profitable innovations. Ram (1987) suggested that when this effect is high, the resistance is high as well.

The above-mentioned innovation characteristics have been grouped into two categories: *Customer Dependent Features* and *Customer Independent Features*. The first category is expected to create the same amount of resistance across all customers, whereas the impact of the second category varies from an individual to another and depends on how they perceive each innovation feature (Kelly & Kranzberg, 1978).

Customer Characteristics

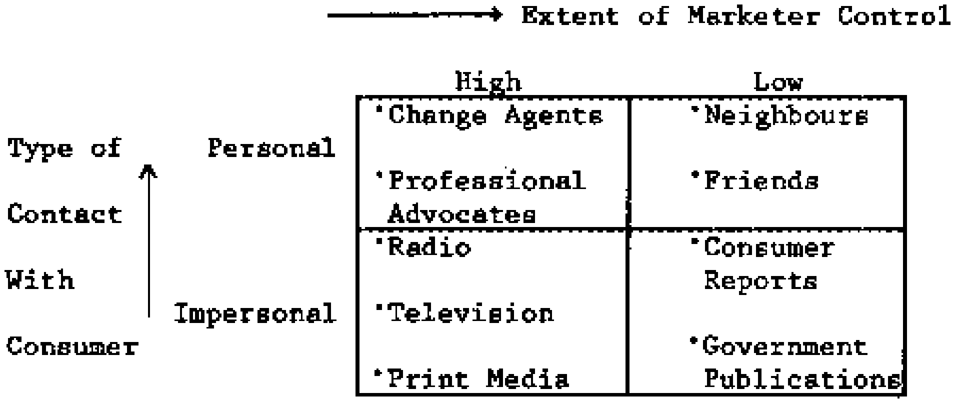
According to Ram (1987), resistance to innovation also depends on customers' particular psychological traits. In the context of innovation, the relevant characteristics that have been identified are: Personality, Attitudes, Value Orientation, Previous Innovative Experience (Brandner & Kearl. 1964), Perception, Motivation (Zaltman & Wallendorf. 1983), and Beliefs (Yeracaris. 1961).

Ram (1987) suggested that customer *personality* is one of the major determinants of innovation resistance. In this context, self-confidence and dogmatism play a critical role. Indeed, high self-confidence customers are more likely to adopt the innovation even if they cannot try it before, whereas high dogmatics are more likely to resist, since they may feel threatened and anxious about the potential changes the innovation will bring (Rokeach, 1973). Customer *perception of the need* to adopt an innovation is another important adoption determinant. If this perception is high, the resistance is lower. Customer's positive *beliefs* and *attitudes* toward adopting an innovation and favourable *previous positive experience* would reduce innovation resistance. "Mindset" is the human tendency to bring a past experience to the present decision-making or problem solving. This bias plays an important role in influencing individual perception and attitudes. One last relevant characteristic is customers' *ability to innovate*. It is strongly related to demographic variables (education, age, income, mobility). Even if the characteristics mentioned above are favourable for innovation adoption, a lack of ability to innovate would cause customer resistance (Ram, 1987).

Characteristics of Propagation Mechanisms

Ram (1987) focused on the role that the mechanisms of propagation play in the context of customer resistance. Robertson (1971) classified propagation mechanisms in two dimensions: the *level of marketer control* and the *type of contact with the customers*. In the first phases of the product lifecycle, the propagation mechanisms, such as advertisements, are highly controlled by the marketer. However, as more individuals adopt the innovation, these mechanisms outside marketer control and begins to be controlled by customers, such as word-of-mouth. Therefore, the earlier the innovation is in its lifecycle, the greater the effectiveness of marketer-controlled propagation mechanisms in reducing innovation resistance. In the subsequent stages, instead, propagation mechanisms not controlled by the marketers have a greater effect on resistance (Ram, 1987). Robertson (1971) highlighted the importance of the characteristic of propagation mechanisms in inducing innovation resistance. The most influential features are: clarity, credibility, informativeness and perceived source attractiveness or similarity. The *clarity* of the propagation mechanism influences individual motivation to search for more information. *Credibility* affects the source perceived expertise. *Informativeness* impacts on customer decision making process. Lastly, *perceived similarity or attractiveness* of the source influences customer receptivity of the information communicated. Specifically, the higher the clarity, credibility, informativeness and the perception of attractiveness or similarity of the source, the lower the innovation resistance (Ram, 1987). Fig. 2.3 indicates different sources of propagation classified along two dimensions: the extent of marketer control (high or low) and the type of contact with consumer (personal or impersonal).

Fig. 2.3. Classification of Propagation Mechanisms



Source: Ram, 1987

2.3.2 *Consumer Resistance to, and Acceptance of, Innovation Model (Bagozzi & Lee, 1991)*

In 1991, Bagozzi and Lee built a comprehensive model to describe customer resistance to, and acceptance of, innovations by focusing on the particular stage of customer information processing with regard to innovations. This model is based on Gatignon and Robertson’s (1991) studies. They identified two categories of factors that are essential for information processing. One group includes all the factors motivating information search (information value, relief of decision anxiety and social definition for consumption) and the other one includes all the factors inhibiting information search (risks of accepting poor information and taking subordinate position). Specifically, Bagozzi and Lee (1991) focused on the part of the theory of customer resistance to innovation that is related to goals. Goals can be defined as “*internal representations of desired states, where states are broadly construed as outcomes, events or processes”* (Austin & Vancouver, 1996, p. 338). Individuals structure goals in cognitive schema of things they want to achieve, or they want to happen. To achieve a desired goal, it is generally required to achieve first a series of sub-goals. According to the two authors (1991), the cognitive schema and the overall goal significantly affect customer decision to adopt or reject an innovation. Specifically, they divided the adoption process in two phases: *goal setting* and *goal striving*.

Goal setting in the context of adoption decision can be structured as a multiple stage process:

- *Stage 1*: the customer has to phase an internal or external change that begins once he is exposed to the communication of an innovation or simply, he discovers it once he come across it. Parallel to this, an internal change involving a recognition of a problem or need may occur. If the individual is stimulated, its response to change can be resistance or acceptance. In case of innovation resistance, to move to the next stage, it is required to break the resistance to change: the customer has to be open to consider the innovation.

- *Stage 2*: it involves the evaluation of the innovation attributes and adoption consequences. The result of this process is the individual perception of an innovation as a threat, an opportunity or both. On the basis of the evaluation, the customer may impulsively decide to adopt it or reject it. However, most people do not take decisions prematurely and tend to continue with the information processing.
- *Stage 3*: it captures further elaboration of one's feelings and thoughts. Emotions are mental states that emerge after one makes appraisals of an innovation features and the consequences of adoption. The perception of an opportunity lead to positive emotions, such as joy, pride, hope and love, that contribute to emotional acceptance of innovations. On the contrary, the perception of a threat lead to negative emotions, such as anger, fear, sadness and shame, that contribute to emotional resistance to innovations. In decision-making processes with respect to innovations, emotions derive from the appraisal of possible alternative consequences the individual imagines may derive from adopting or not adopting the innovation and their congruence or incongruence with desired goals. These anticipatory emotions play a key role in the decision-making process (Bagozzi et al. 1998; Roseman et al., 1990). Emotions can also be influenced by other cognitive processes like the individual confidence that he or she is able to do what it takes to adopt an innovation (self-efficacy) (Bandura,1991) and the outcome expectances, defined as one's likelihood judgements that, by acting, the goal will be achieved.
- *Stage 4*: it encompasses coping responses. Coping responses deal with information integration of the feeling and cognitive responses and the related felt action tendencies. According to Lazarus (1991) there are two main forms of coping strategies: under *problem-focused coping*, that occurs when an individual relies on action-centred responses to reduce decision making stress, and *emotion-focused coping* that occurs when an individual relies on cognitive-centred strategies to control the emotional responses. Adoption or rejection of an innovation can be though as functions of coping responses and their associated action tendencies (Bagozzi, 1992). Action tendencies can be defined as an automatic and adaptive type of coping each of which is connected to a specific emotion (Frijda, 1986). In this regard, four general decisions can be made with respect to an innovation: adopt the innovation, try the innovation, resist adoption and postpone the decision (undecision). For what concern resistance, individual may be comfortable with this decision, and so adoption will never occur. Alternatively, they may be aware that, for

some reasons, it will be overcome in the future. Indecision may results from an incomplete information integration process and can be caused by the high complexity of the decision or by the approach avoidance/conflict that cannot be overcome.

Bagozzi and Lee (1991) argued that the adoption process does not end after the decision has been made. Therefore, they included in the model the aspect of decision implementation and structured the implementation process in five goal-striving stages:

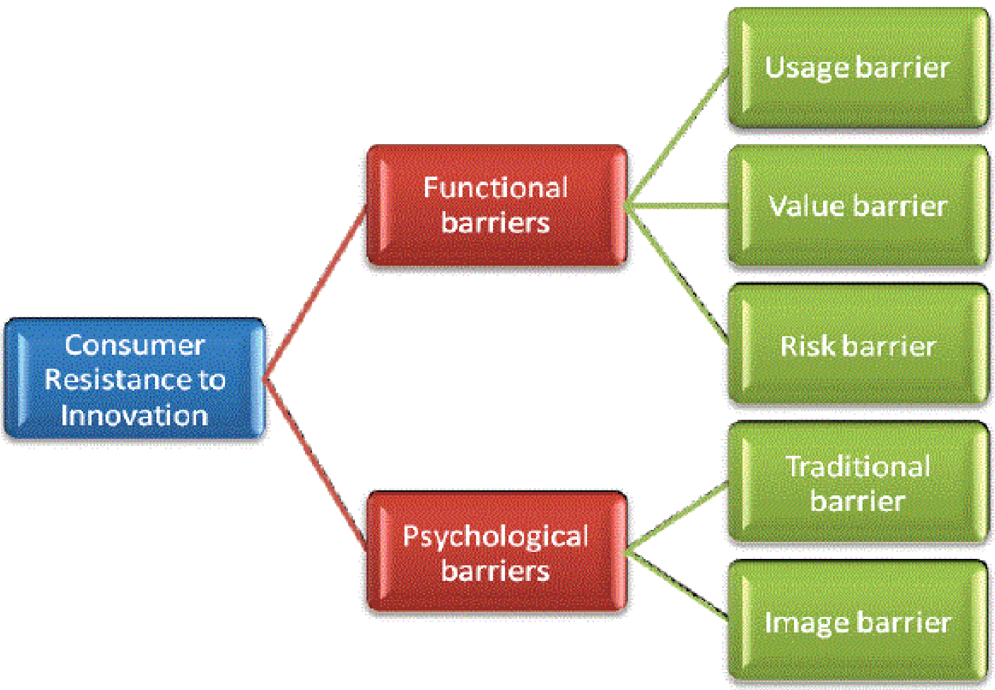
- *Appraisal and choice of means for goal striving:* it consists in deciding how to fulfil the decision. It begins with the evaluation of possible alternative means. The appraisal process can be based on one's confidence towards the execution of one specific mean, the means-outcome expectancy for each possible mean or the affect or degree of liking or disliking each option. The choice will depend on the integration of the results that derive from the three appraisals (Bagozzi & Edwards, 1998).
- *Action planning:* according to Gollwitzer (1996), planning consists in deciding when, where, how and how long to act. These sub-plans in each decision point connect situational cues to instrumental acts needed to implement the adoption decision.
- *Initiation of goal pursuit:* it consists in realizing the intended plan by executing goal-directed behaviours as the anticipated situational cues emerge.
- *Control of goal pursuit:* when implementing the plan it is critical to control the activities by performing four general sub-activities: overcoming any impediments that may arise, resisting goal-thwarting temptations, maintaining one's motivation and commitment to goal attainment and re-evaluating one's goal, means and alternative goals during pursuit.
- *Actual adoption or rejection:* adoption or rejection is strongly influenced by successful choice and implementation of means. However, the adoption or rejection decision will be appraised as well and the adoption-outcome emotions will be generated on the basis of the extent to which the actual outcome differs from the desired one. These emotions are used to regulate goal setting and goal striving activities to manage repeat purchase behaviour in the future (Luce, 1998).

In summary, Bagozzi and Lee (1991) developed a theoretical model that can explain customer resistance to innovation by structuring it as a purposive behaviour activity, framed with two decision activities (goal setting and goal striving), in which one's personal traits and the situation influence the processing of information about an innovation. They suggested that it is critical to focus on both customer resistance and acceptance and the ways they are integrated during the decision-making process. An important contribution for the literature on customer resistance is the emphasis they gave to the role played by emotions in the adoption or rejection decisions.

2.3.3 *Consumer Resistance to Innovations Model (Ram & Sheth, 1989)*

Ram and Sheth in 1989 built a theoretical model to explain customer resistance to innovation. This model was based on the assumption that individual tend to resist novelty for two main reasons. First, it threats their satisfactory status quo and established routines with a potential change. Innovations that create a significant change for an individual are said to be discontinuous. The higher the discontinuity the higher the resistance it will encounter. Second, a new product may conflict with their prior belief structure. The more the conflict, the higher the resistance. This model has been largely used in previous literature in the context of active innovation resistance (Heidenreich et al., 2016; Laukkanen, 2016; Mani & Chouk, 2016; Talke & Heidenreich, 2014) and has found literature support for both product and service innovations (Laukkanen, Sinkkonen, & Laukkanen, 2008). However, two limitations characterize this model. First of all, it is based on past concepts since it has not been adjusted to the digital age. Second, it only focuses on situational antecedents of resistance and does not take into account the personal predisposition (Heidenreich & Handrich, 2015, Roux 2007) and demographic variables (Laukkanen 2016). The two authors identified five customers' adoption barriers and grouped them in two categories: *functional barriers* and *psychological barriers*. Fig. 2.4 provides a graphical representation of the model.

Fig. 2.4. Customer Resistance to Innovation model



Source: Ram and Sheth, 1989

Functional Barriers

Functional barriers arise when customers perceive that by adopting the innovation, they would experience a significant change. These barriers deal with three areas: product usage patterns, product value and risks associated with product usage.

Usage barriers arise when an innovation conflicts with an individual established routines, habits or existing workflows. Habit is usually one of the main causes of passive resistance. Sheth (1981) terms this "*the single most powerful determinant in generating resistance"* and notes that "*perceptual and cognitive mechanisms are likely to be tuned in to preserve the habit because the typical human tendency is to strive for consistency and status quo rather than to continuously search for, and embrace new behaviors"* (p. 275). Specifically, the higher the changes in individual's routine caused by the innovation, the higher the resistance it will encounter (Herbig & Day, 1992). These resistance mechanisms can be associated to the attitude strength toward the object of habit, perceived difficulties and challenges, and TAM's perceived ease of use and complexity of the innovation. Also, according to Laukkanen et al. (2007), this barrier is strongly associated to the innovation's usability. According to Eagly and Chaiken (1995), the extent of attitude strength may depend "*on prior evaluative experience and the link with other more abstract attitudes"* (p. 248). It may reduce the receptiveness to an innovation: the higher the attitude strength, the fewer the individual is open to change and to adopt innovations. Perceived difficulties and challenges of technology use refer to the cognitive effort that the adoption requires (Ram, 1989) and if they are higher than the expected benefits customers are more likely to resist (Poo & Dalziel, 1989). TAM's ease of use and complexity are related (Hoeffler, 2003) and deals with the difficulties of using and understanding the new technology (Kleijnen et al., 2009). The higher the perceived complexity, the higher the learning cost required (Hoeffler, 2003) and the more customers will tend to resist. The significant effect of the perception of innovation complexity on customer decisions has found large support in literature (Antioco & Kleijnen, 2010; Kuisma et al., 2007; Laukkanen, 2016). For example, the small screens of mobile devices would make reading and typing texts quite complex and it may discourage adoption (Bruner & Kumar, 2005; Laukkanen, 2016). Arts et al. (2011) have found this factor to be one of the most influential antecedent of adoption behaviour. Usage barriers resulted to be particularly relevant in the internet banking (Kuisma et al., 2007) and bill payment via mobile phone (Laukkanen & Lauronen, 2005) context.

Value barriers deal with the customer perceived value of the innovation and whether the new product or service is better than existing offering to induce customer to replace them (Ferreira et al., 2014). Specifically, if the innovation does not offer a better performance-to-price ratio than the product substitutes, it would encounter a high resistance. Customers perceive the price as a monetary sacrifice (Kim et al., 2007) and what is given up obtaining the innovation (Zeithmal, 1988). Studies evidence that a low performance-to-price ratio is the most significant obstacle for consumers to adopt innovations (Parasuraman & Grewal 2000). Antioco and Kleijnen (2010) have demonstrated that the lack of perceived value has a negative impact on customer adoption decision toward a technology (Ferreira et al., 2014). This barrier is particularly relevant in the context of service innovation (Laukkanen, 2016) and technological innovation adoption (Kim et al., 2007). It can be associated to the relative advantage identified by Rogers (1995) in his Diffusion of Innovation model as one of the five characteristics influencing customer acceptance of innovation. In the IoT context, customers are mainly concerned of potential additional costs due to installation, repairs and maintenance (Balta-Ozkan et al., 2013) and the low economic benefits (Touzani et al., 2018). Therefore, this barrier has been found to be one of the main causes of the slow adoption rate of smart services (Hoffman & Novak, 2015). The value barrier also resulted to be particularly relevant in the context of the internet banking (Laukkanen, 2016). Kuisma et al. (2007) research revealed that for nonusers the relative advantage of this service is poor, since it has high costs associated to the purchase of the computer and the internet connection.

Risk barriers are defined by Dowling and Staelin (1994) as "*consumer's perceptions of the uncertainty and adverse consequences of buying a product (or service)"* (p.119). Fain and Roberts (1997) argued that the risks embedded in an innovation is rather a perception of the individual than a characteristic of the product. They arise due to the uncertainty and potential negative consequences associated to the adoption of an innovation that cannot be anticipated (Ram & Sheth, 1989). When customers are aware of the risk, they tend to delay the adoption in order to search for additional information and learn more about the new product. It is possible to list four main risks. *Physical risk* it is related to the possibility that the innovation may harm a person or a property. *Economic risk* arises when the cost of an innovation is high. *Functional risk*, related to the performance uncertainty, arises when the individual cannot test the product before purchasing it and, thus, one is worried that it may not function properly. *Social risk* arises when customers feel that by adopting the innovation, they may be isolated or ridiculed by peers. The relevance of this barrier, as a significant obstacle in the adoption process, has found large support in previous research (Klerck & Sweeney, 2007). Kleijnen et al. (2009) has identified the economic risk as one of the main drivers of resistance. In the service context, Laukkanen (2016) has provided evidence of the significant effect of the security risk, known as the concern of losing control over personal or private information (Kleijnen et al., 2007), on customer behaviours. Several studies have also highlighted the perception of this risk associated to the use mobile devices connected to the Internet (O'cass & Fenech, 2003). Indeed, evidence shows that it is one of the major barriers in the adoption of smart services and smart products (Shin & Park, 2017). In the context of online shopping, security risk relates to system security and fraudulent behaviour by online retailers and it is perceived more by individuals that are less expert in the use of Internet (Miyazaki & Fernandez, 2001). Perceived health risk is another significant driver of customer resistance to innovations. Several researches have proved the negative effect that electromagnetic waves and radiation, produced by technologies, have on humans (Burgess, 2002). In 2004, mobile phones have been classified by the World Health Organization as drivers of cancer. Therefore, the proliferations of highly technological devices and their pervasive presence in our life increase perceived health risks and the related customer concerns. The smart products require a constant connection to the Internet and, thus, individual may perceive a high health risk in the usage of such devices. Therefore, customers tend to perceive such devices as possible threats to their well-being rather than as opportunities (Marakhimov & Joo, 2017). With regard to mobile banking, risk of making mistakes when conducting bank activities via a mobile device and the privacy and security risks resulted to be two of the major concerns (Laukkanen & Lauronen, 2005). In this context, security deals with the fear of financial loss and it is also influenced by the internet banking context confidentiality (Liao & Cheung, 2002), whereas privacy is related to the fear of unethical management of personal data and the theft of private information during online transactions (Paylou, 2003). Other concerns in this field are related to connection breaks during transactions (Black et al, 2001) and the possible loss of portable list of PIN codes (Kuisma et al., 2007). According to Ram and Sheth (1989), these fears contribute to create risk barriers and explain customer resistance to innovations.

Psychological Barriers

Psychological barriers relate with the conflict the innovation create with customer's prior beliefs. These barriers deal with two main factors: the traditions and norms of individuals and the perceived product image.

Tradition barriers arise when customers perceive that the innovation threats their culture and tradition and it is incompatible with their existing value, past experiences and social norms. The greater the deviation from established traditions required by the adoption of an innovation, the greater the resistance it will encounter. This concept find support in the Theory of Reasoned Action (TRA) (Ajzen & Fishbein, 1980) that illustrates the importance of social norms and the opinion of relevant others in adoption decisions (Kulviwat et al., 2009). The strong resistance reactions towards innovations caused by tradition barrier range from negative word of mouth to boycotts and sabotage (John & Klein, 2003). Tradition barriers can be explained by customers tendency to resist replacing an old product with a new one when they have developed positive attitudes toward it (Wang et al., 2008). In the service context, it can be associated to the customer need to have a certain degree of human interaction (Laukkanen & Kiviniemi, 2010) and to avoid machines (Dabholkar & Bagozzi, 2002) during the service experience, since it represents a social opportunity both for customers and sales personnel (Dabholkar, 1996). Prior literature on this topic has emphasized the importance of this aspect in the service context (Evanschitky et al., 2015; Walker & Johnson, 2006). Research reveals that the need for human interaction has a negative impact on self-service technology adoption (Marr & Prendergas, 1993) and also discourage customers decision to use (Walker & Johnson, 2006) or continue using (Evanschitzky et al., 2015) service-related technologies. Tradition barriers seem to be particularly relevant in the IoT context, in which intelligent devices are able to perform tasks autonomously without the human intervention and arise especially in relation to smart services (Mani & Chouck, 2018). Prior research evidence the relevance of this barrier in the electronic banking field, since individuals are not used pay with these systems and they may prefer to interact directly with the bank clerk instead of using arms-length technologies (Fain & Roberts, 1997; Heinonen, 2004; Forman & Sriram, 1991).

Image barriers arise in relation to an unfavourable innovation image the customer perceives due to association between the innovation identity and its origins (product class, industry or country of manufacture). It makes the life quite difficult for an innovation, since it is related to a perceptual problem linked to a stereotyped thinking and a lack of information (Ram & Sheth, 1989). An unfavourable media coverage can lead to a low perceived image that results in an innovation resistance (Kleijnen et al., 2009). The image barrier can be considered as an extrinsic cue that influences customer's assessment of a new product (Bearden & Shimp, 1982). As a consequence, if customers negatively perceive the extrinsic cue, they will develop a negative image and this will create a barrier (Ram & Sheth, 1989). This barrier can also arise in case of lack of self-image congruence between the individual image and the innovation image. The innovation image is originated from a set of personality attributes and psychological associations (Sirgy, 1985). According to the self-congruity theory (Sirgi, 1985), self-image congruence is a key psychological determinant in customer decision-making process. Several prior researches provided evidence of the significant impact of self-image congruence on behaviours (Coward et al., 2008), attitudes (Graeff, 1996) and the perception of service quality (Hosany & Martin, 2012). It was applied in the context of adoption of new products and services (Kleijnen et al., 2005) and attitude formation toward e-book (Antòn et al., 2013). Two possible negative images, that can trigger off resistance towards the IoT devices, are the perception of "gadgetry" (Balta-Ozkan et al., 2013) and the lack of perceived added value (Mani & Chouk, 2017). This barrier has found support in Laukkanen (2016) research for what concern the adoption of mobile banking and in Strebel et al. (2004) study with regard to the adoption of high technological durable goods.

2.4 Customer Resistance to Innovation: *Studies in the Internet of Things (IoT) context*

In the academic field, issues related on the IoT have been largely discussed. Most of studies have predominantly focused on overview descriptions, concepts, opportunities, challenges and business models (Chiu et al., 2010; Gubbi et al., 2013; Vermesan et al., 2011). These researches have addressed critical issues such as standards, architectural elements and enabling technologies. However, despite the rapid growth of IoT devices and IoT-based services, academic investigation of the determinants of IoT adoption and resistance, from the user perspective, is still in an early stage. In the existing literature on resistance, Ram and Sheth's model (1989) is the theoretical framework that has received the greatest consideration and through its extensions (Mani & Chouk, 2018) and applications (Mani & Chouk, 2017; Laukkanen et al., 2007; Laukkanen, 2016) it has been possible to obtain interesting results relative to the Internet of Things (IoT) context, specifically with regard to the drivers of customer resistance towards smart products and smart services.

In the successive sections some of the most significant findings that have been extracted from an analysis of the academic literature are discussed.

2.4.1 *Mani & Chouk (2018)'s Model*

Mani and Chouck (2018) developed a conceptual model to explain customer resistance to innovation in the smart service context by using Ram and Sheth's model (1989) as theoretical foundation, in line with previous research within the marketing literature that have applied this model to investigate customer barriers towards technological innovations in services (e.g. Laukkanen, 2016; Laukkanen et al., 2008). They adapted Ram and Sheth (1989)'s model to the digital age, investigated customer resistance from an ideological perspective and recognized the relevance of dispositional variables. Specifically, the two authors (2018) enriched the original model by including three new types of barriers: *technological vulnerability barriers* (technology anxiety, technological dependence), *ideological barriers* (skepticism) and *individual barriers* (inertia).

Technological Vulnerability Barriers

The rapid technological developments over the last 20 years contributed to change significantly individual's attitudes and beliefs. Customers have to confront and interact continually with technology, which is now embedded in all areas of human life. Ram and Sheth's model (1989) did not take in consideration the digital age and the latest continuous technological revolutions. In order to overcome this huge limitation, Mani and Chouk (2018) enriched the model by adding technology vulnerability barriers, a new category of psychological barriers.

Vulnerability can be defined as a state of helplessness, loss of control and dependence (Baker et al., 2005). This state is enhanced as the importance of technology grows in our society leading to negative emotions, technostress, technophobia and much more (Shu et al., 2011). Anxiety and dependence are among the most impactful technological emotions. Therefore, according to Ram and Chouk (2018), technology vulnerability barriers are mainly driven by the perception of technological dependence and technology anxiety. In their study, they refer to technological dependence "*as a psychological state that provides a sense of being overly dependent on, and a feeling of being enslaved by, technology*" (Ratchford & Barnhar, 2012, p. 1212) for accomplishing tasks or reaching specific goals. It is also influenced by the perception that the use of technology reduces autonomy. Several cyber-psychology studies (Lu, 2008; Young, 2004) revealed the negative impact of dependence of new information and communication technologies on humans. Isolation (Davis, 2001), technostress (Shu et al., 2011) and addiction (Charlton, 2002), defined as a pathological state caused by the abuse and overuse of technology (Dhir et al., 2015), are among the most serious consequences. Ratchford and Barnhart (2012) highlighted that customer feeling of dependence grows with the continuous advances of technology and introduced the *Technology Adoption Propensity Index* which decreases as the perception of technology dependence increases. Literature evidence the development of dependence in relation to mobile phones (Licoppe & Heurtin, 2001), online video games (Lo et al., 2005) and the Internet (Hadlington, 2015). In particular, the IoT devices, that are continuously connected to the Internet, can easily create psychological and functional dependence (Mani & Chouk, 2017). Technology anxiety is associated to the feeling of fear and apprehension for the use of new technology (Igbaria & Parasuraman, 1989) and it is the opposite of the *Technology Readiness Index*. This metric, introduced by Parasuraman (2000), indicates individual's willingness to adopt technological innovations. Technological anxiety was defined by Venkatesh (2000) in relation to computers as "*an individual's apprehension, or even fear, when he is faced with the possibility of using the computer*" (p. 349). Therefore, this negative feeling can give rise to psychological barriers that discourage customer adoption. Evanschitzky et al. (2015) provided evidence that technological anxiety lead to resistance in the context of customers' trial of service innovation. Touzani et al. (2018) highlighted that the IoT devices can create a state of anxiety. In line with this finding, Mani and Chouk (2018) suggested that the proliferation of IoT devices in all domains generates technological anxiety and leads customers to resist adoption.

Ideological Barriers

Ideological barriers arise from an individual personal conviction related to a set of negative ideas about an innovation that conflicts with their beliefs and values. This situation leads customers to become skeptical toward the benefits of the new technology (Kleijnen et al., 2009). Skepticism refers to individual tendency to doubt, question and disbelieve (Bunge, 1991). Generally, marketing literature focuses on investigating the main causes of customer skepticism towards companies' persuasion techniques (Obermiller & Spangenberg, 2000) or new products (Morel & Pruyn, 2003). Mani and Chouk (2018) refers to skepticism as a psychological barrier that cause customer resistance towards the IoT devices and the related promised benefits. Skepticism can be directed to marketing discourses, aimed at promoting the new IoT devices, to prospective discourses, aimed at highlighting the revolutionary features of the IoT devices and to prescriptive discourses, aimed at emphasizing the technical and functional aspects of the IoT devices. To investigate customer skepticism, Skarmeas and Leonidou (2013) used the *Attribution Theory*. This theory explains how individuals attribute causes to events and how their attitudes and behaviors are influenced by the perceptions they have about these attributions (Heider, 1958). Mani and Chouk (2018) used the Attribution Theory to explain customer skepticism towards smart services. Specifically, they suggested that skepticism influences customer resistance through attributional mechanisms (inertia, technology anxiety and perceived dependence). In prior research, skepticism has been studied as an antecedent of resistance (Roux, 2007). However, academic findings provide evidence of its new mediating role between technological vulnerability and individual barrier on customer resistance and this is probably one of the major contributions of Mani and Chouk (2018) research. Furthermore, the development of information and communication technology (proliferation of commercial information technologies) and anti-market activist networks (proliferation of commercial counter-discourses) contributes to the creation of this barrier (Mani & Chouk, 2018).

Individual Barriers

Individual barriers enable to explain the individual predisposition to resist change (Heidenreich & Handrich, 2015; Kleijnen et al., 2009). Customer resistance is not only influenced by contextual factors since also individual factors play a critical role (Heidenreich & Handrich, 2015). Polites and Karahanna (2012) associated this tendency to the concept of inertia, defined as individual predisposition to prefer the status quo rather than going through uncertain changes (Mani & Chouk, 2018). Individual barriers can lead to two different types of resistance: active and passive (Heidenreich & Handrich, 2015). Active resistance is related to "*a negative attitude formation driven by functional and psychological barriers that follows deliberate new product evaluation"*

(Heidenreich & Handrich, 2015, p. 881). Passive resistance refers instead to the "*predisposition to resist innovations due to an individual's inclination to resist changes and status quo satisfaction that already forms rather unconsciously prior new product evaluation"* (Heidenreich & Handrich, 2015, p. 881). Heidenreich and Spieth (2013) demonstrated that the higher the propensity to resist change, the greater the effort required to overcome resistance. Furthermore, they argued that when individuals are satisfied with their status quo, they also tend to be satisfied with the current products or services and, therefore, they will be less likely to substitute them with an innovation. This particular barrier can be explained by the *Status Quo Bias*, a behavioural bias that explain human tendency to resist change because any novelty is perceived as uncertain and risky. Samuelson and Zeckhausen (1988) associated this behaviour to people's predisposition to minimize losses. This theory has also been applied by Kim and Kankanhalli (2009) in the Information System research to investigate user resistance towards IS-related changes and results emphasized individual tendency to resist information system adoption in order to maintain their status quo. Mani and Chouk (2018), in their study, suggested that inertia contributes to create individual barriers and drives customer resistance towards innovations.

The research Mani and Chouk (2018) conducted to examine adoption barriers towards smart services provided interesting results. With regard to functional barriers, perceived complexity resulted to be one of the major cause of the rise of usage barriers. Perceived price did not significantly influence customer adoption or rejection decision. The study confirmed the influence of risk on innovation resistance, in particular perceived health and security risks appeared to be the main drivers of resistance. Perceived health risks is particularly high for those individuals aware of the IoT devices ubiquity that are source of electromagnetic radiation and expose them to a large volume of radiations. Security risk, in the context of smart services, resulted to be associated to the fears of being hacked and the theft of sensitive data. With regard to psychological barriers, individuals resulted to give particular attention to the compatibility between their self-image and the image of the smart service. Some customers perceived a gap between their image and the smart service image (image barrier), seen as luxuries or "gadgetry". The research also revealed that the need for human interaction is another important driver of customer resistance. This insight is particularly relevant in the context of smart services, characterized by the automation of tasks. For what concern technology vulnerability barriers, Mani and Chouk (2018) suggested that technology dependence and anxiety do not impact directly on smart service resistance, but their effect is mediated by the skepticism toward the IoT. Therefore, skepticism plays a central role in mediating the impact of the perception of technological vulnerability barriers towards IoT on customer resistance. Finally, the study revealed that inertia leads individuals to prefer the current situation and to resist innovation, particularly in case of uncertainties within a smart service context.

2.4.2 *Other relevant studies*

Ram and Sheth's (1989) model have found evidence in Mani and Chouk (2017) research aimed at identifying the main drivers of active customer resistance towards smart objects. Specifically, they conducted their study on French "digital natives" and investigated about the smartwatch, due to its increasing popularity (Kim & Shin, 2015). The two authors identified seven resistance drivers that can be grouped in two categories. Usefulness, novelty, price and device intrusiveness can be classified as product characteristics that cause functional barriers. Self-efficacy, dependence and privacy concerns can be classified as customer characteristics that cause psychological barriers. *Perceived usefulness,* defined as the degree to which an individual perceives that the usage of a given innovation could improve the performance, is one of the key variable in the Technology Acceptance Model (David, 1989). It has been found to be one of the major drivers of customer adoption of Internet devices. With regard to smart products, perceived usefulness refers to the benefits the customer thinks will receive from the use of the device, such as saving time, convenience, access to additional information and new uses. Therefore, the absence of these characteristics would cause customer resistance. *Perceived novelty* is a fundamental characteristic of any innovation to be perceived as such (Rogers, 1995). This perception differs largely across individuals and types of innovation. Existing research has considered this factor as an important determinant that predict individual's attitudes towards an innovation, especially in the IT field (Wells et al., 2010). *Perceived price* deals with individual perception about the price of the product (Zeithmal, 1988) and, in the context of innovation resistance, it refers to the perceived value. Therefore, customers tend to resist innovation when it does not offer a good performance-to-price ratio (Ram & Sheth, 1989) or when its price is seen as too high (Lian & Yen, 2013). *Intrusiveness* refers to technology's capability to enter in customers' life without their permission (Mani & Chouk, 2017) and it is considered to have a negative impact on individual behaviour, since it leads to negative emotional reactions, like the feeling of irritation in the case of advertising (Edwards et al., 2020). Smart products may be perceived as highly intrusive, since on the basis of Hoffman and Novak (2015) definition, they can perform tasks autonomously without the permission of the user. Prior research evidence the negative impact that intrusiveness has on customers'adoption of RFID (Boeck et al., 2011) or of mobile location-based services (Hérault & Belvaux, 2014). *Self-efficacy* refers to the individual's perception of his or her ability to use technological innovations (Compeau & Higgins, 1995). Prior research evidenced the existence of a negative link between self-efficacy and innovation resistance (Ellen et al., 1991) and of the positive link between self-efficacy and willingness to adopt technology (David et al., 1989). *Dependence* refers to individual's tendency to rely upon technology to reach their goals (Park et al., 2013). Lastly, *privacy concern,* related to the protection of private and personal information, resulted to be particularly relevant in the context of online transactions (Ashworth & Free, 2006). Previous research highlighted that these concerns will increase as smart products (Slettemeas, 2009) and smart services (Hsu & Li, 2016) develops. These technologies are characterised by pervasiveness, invisibility, ubiquity and invasiveness (Slettemeas, 2009). They collect and manage a huge amount of data and personal information (Sicari et al., 2015). Therefore, research note that privacy concerns negatively influence attitudes towards smart products (Muller-Seitz et al., 2009) and the continued intention to use IoT services (Hsu & Lin, 2016). Mani and Chouk (2017) findings show that perceived usefulness, perceived novelty, perceived price, intrusiveness, privacy concerns and self-efficacy have a significant impact on customer resistance towards smart products. The dependence variable was discarded probably because their sample, composed by digital natives, may have difficulties in perceiving their dependence on technology. The two authors also found that privacy concern has an impact on intrusiveness perception. Reppel and Szmigin (2010) have provided evidence that customer need to perceive they have a certain degree of control on their personal data and the perception of a possible intrusion negatively impact trust (Sill, Fisher & Wasserman, 2008). Since smart objects can collect automatically personal data, individuals may feel skeptical toward them due to concerns related to privacy and intrusiveness that increase when companies can access this information. This can create a huge psychological barrier that leads to smart product resistance. Perceived price seems to be one of the main reasons of resistance to smart products, due to their generally high price. Findings also demonstrates that it is critical for customers to perceive that they are able to understand how smartwatch works. Thus, in line with previous study (Ellen et al., 1991), self-efficacy has a significant impact on resistance.

Laukkanen (2016) used Ram and Sheth (1987)'s model as theoretical lens to investigate the factors influencing customer adoption, postponement and rejection behaviour toward the Internet and mobile banking service innovation and extended the model by adding demographic variables (age, gender and income). He tested three models in which the dependent variables are: mobile banking adopters versus non-adopters, mobile banking postponers versus rejectors and Internet banking postponers versus rejectors. Interesting results emerged. The value barrier was dominant in the three models. In line with this finding, previous literature considered usefulness as the most important driver of customer's decision to adopt Internet banking (Hanafizadeh et al., 2014), whereas usage complexity and perceived risk do not impact on non-adoption or postponement of Internet and mobile banking services. With regard to psychological barriers, the image barrier was found to negatively impact the adoption of mobile banking, whereas tradition barrier negatively influences Internet banking adoption. One of the major finding is the evidence of the critical role that customer demographic plays in the adoption and rejection behavior towards these services. However, these findings are discussed in the next section.

Hsu and Lin (2016) studied the impact of network externalities and privacy concern in the IoT usage. Network externalities can be defined as "*the value or effect that users obtain from a product or service that will bring about more value to consumers with the increase of users, complementary products or service"* (Katz & Shapiro, 1985). Therefore, the value of any smart device increases as the number or users or complementary products increases. Prior studies have distinguished between direct and indirect network externalities (Gupta & Mela, 2008, Katz & Shapiro, 1985). Direct network externalities relate to the perceived critical mass of users, defined as the "*degree to which a person believes that the mass of people would use IoT"* (Hsu & Lin, 2016, p. 519), and the number of IoT services available. Accordingly, the perceived value or usefulness of the IoT service increases as the number of service points in which the IoT service is available and the number of users increases. Metcalfe's law stated that the network's value is the square function of the number of its users. Therefore, in the Internet, the more users access it, use it, share information and participate to the network activities, the more the value perceived, and the perception of the critical mass will be reinforced. Indirect network externalities, also called cross-product network externalities, depend on the number of available complimentary products and services and the perceived compatibility. Perceived complementarity can be defined as "*the availability of function or applications serving to fill out or to complete IoT services"* (Hsu & Lin, 2016, p. 519). Specifically, prior studies evidence that when complementary products or services to a primary product increases in supply or they are sold at a lower price, then the perceived value and the demand of the primary product increases as well as (Lin & Bhattacherjee, 2008). In the IoT context, there are a myriad of complimentary applications and functions, such as identification, transactions, payment of parking fees, control access, shopping coupons and much more. In line with prior research, Hsu and Lin (2016) suggested that the presence of these applications positively influences individual's life convenience and work efficiency. Perceived compatibility is defined as "*the degree to which an IoT is perceived as being consistent with the existing values, need and past experiences of potential adopters"* (Hsu & Lin, 2016, p. 519). Prior studies have emphasized the relevance of compatibility as a critical driver of innovation adoption (Tan & Teo, 2000; Cooper & Zmud, 1990). According to the Diffusion of Innovation theory (Rogers, 1983), it motivates the majority of individuals. Therefore, users are less willing to adopt technologies that lack compatibility (Chiu et al.., 2013; Gandal, 1994; Lin et al., 2011). Gandal (1994) found that individual willingness to pay for IT products or services increases as the number of existing users and compatibility with other application increases. The latter has been found to be a critical determinant of continued intention to use social network sites (Chiu et al., 2013). Privacy can be defined as "*the right to select what personal information about me is known to what people*" (Westin, 1968). With the proliferations of IoT products and services characterized by a continuous exchange of information and data, privacy has become a critical issue. Ziegeldorf et al. (2014) proposed that IoT service providers should guarantee the following three types of privacy: awareness of the privacy risks imposed by smart things and services surrounding the data subject, individual control over the collection and management of personal information and, lastly, awareness and control of subsequent use and spread of personal data by these parties to any entity outside the data subject's control. To reduce customer resistance towards the IoT products and services due to privacy concerns, Miorandi et al. (2012) recommended service providers to define a general model for privacy in the IoT, develop innovative enforcement techniques and find some ways to balance the need of anonymity with the need of localization. Privacy concerns can be related to data collection, unauthorized secondary use, improper data access and errors (Smith et al., 1996). Specifically, these concerns relate to the perception that an excessive amount of personal information are collected by IoT service providers, that unauthorized third parties can access and use these data for unspecified purposes and that unappropriated procedures are applied to protect data from accidental or deliberate errors during collection (Steward & Segars, 2002). Interesting findings emerged from Hsu and Lin (2016) research. Perceived critical mass, compatibility and complementary resulted to have a significant impact on perceived benefits that, in turn, contribute to predict attitudes towards the adoption and the continuous usage of the IoT services. Perceived compatibility resulted to be the most important determinant of adoption decisions, since it can reduce the related uncertainty, thus reducing the risk barrier. Perceived complementary with other products and services appeared to be an important predictor to form positive attitude towards the IoT services and therefore it has a positive impact of adoption. This variable resulted to have a major influence on user's adoption intention than the available number of IoT service points that was found to have no significant effect on perceived benefits. According to Hsu and Lin (2016), one possible explanation would be that nowadays individuals perceive that such IoT products and services are quite ubiquitous in their lives and thus the number of available IoT service points has not a significant impact on the benefits they perceive. However, users give a major consideration to the availability of complementary products and services provided at each service point. With regard to privacy, evidence shows its critical role in shaping user's intention to adopt. Specifically, improper access and unauthorized secondary use are the main cause of privacy concerns. Therefore, this finding suggests that IoT users are particularly worried of unauthorized access and use of their personal information.

2.4.3 *The role of demographic variables*

In order to have a more comprehensive theoretical framework, it is worth considering the role that demographic variables (*age, gender, income*) play in driving consumer resistance towards innovations. Demographic variables are critical predictors of consumer behaviour with regard to adoption and rejection and intention-to-use decisions (Rogers, 1983; Vankatesh et al., 2003). Therefore, recognizing and tracking demographic changes is critical for marketers, since they have significant long-term implications for marketing and business strategies (Oumlil et al., 2000). Aging of population is one of the latest demographic trend that most of industrialized countries are experiencing. It is visible in the increase of the proportion of elderly people as a percentage of the total population. This phenomenon can be explained by an increased life expectancy and the high bird rates during the years 1946 and 1964 (Moschis, 2003). The term used to define people falling into the elderly segment is “mature customer” (Kennett et al., 1995). However, there is not a unique definition for this category. Some studies restrict this segment to people over 50 years of age (Bartos, 1980), some others consider those over 55 years of age (Kennet et al., 1995; Moschis et al., 2004; Laukkanen et al., 2007) and some consider those over 65 years of age (Mattila et al., 2003; Oumlil et al., 2000). The process of aging involves two types of changes: biophysical and psychosocial (Kennett et al., 1995). Biophysical aging is an easily observable change and it is related to the individual ability to process information with regard to the manner and speed. It is usually associated to physical and health issues, like a decline in vision, loss of acuity, decline in colour sensitivity and much more (Kennet et al., 1995). Psychosocial is related to a psychological and a social change. Psychological aging occurs when an individual perceives of being an old. Social aging occurs when the individual perceives the roles associated with the old age (like being a retiree) (Moschis, 2003). Thus, aging involves a number of changes in human life: emotions change, need for products and services changes as well as their perceptions and responses to marketing stimuli (Moschis, 2003). However, people reactions to aging may change on the basis of two different attitudinal perspective: personal perception and public perception. Personal perception refers to how older people see themselves, whereas public perception refers to how other people see aging customers (Moschis, 2003). Today the mature market deserves the attention of companies in every field, since it is constituted by an important customer segment, whose consumption behaviours and attitudes cannot be ignored (Laukkanen et al., 2007). Previous research evidenced that they have a higher purchasing power than other people, invest more and spend more on luxury products (Kennet et al., 1995; Moschis, 2003). In order to serve the mature market, companies have to examine the barriers that cause elderly people to resist innovations (Laukkanen et al., 2007). Ferreira et al. (2014) noted the influence of age, income and gender on customer acceptance and adoption of technological innovation. A number of studies have focused on investigating elderly people behaviour towards new technologies, such as computers, the internet and mobile phone. Evidence show that mature consumers are becoming more familiar with technology and they are willing to try new products, but for different reasons than youngers customers. The main driver of mature customers is the need, whereas youngers are more driven by the desire to try something because it is trendy (Leventhal, 1997). Laukkanen et al. (2007) conducted a study to explore how innovation resistance in the mobile banking context differs between mature customers and younger customers and used Ram and Sheth (1989)'s Resistance of Innovation model as theoretical lens. They found that the most significant determinant preventing mobile banking adoption among mature customers is the value barrier. Elderly non-users mobile banking innovation did not perceive a better performance-to-price value compared to its substitutes. Surprisingly, tradition barrier did not result a reason for resistance since self-service innovations in banking appeared to be even preferable to the traditional bank branch. In comparison to younger segment, mature internet banking customers differ with regard to risk, tradition and image barriers. Indeed, usage and value barriers resulted to be equally perceived for both segments. In line with previous research, that evidence mature people tendency to avoid risk (Brock, 1998), risk barriers resulted to be significant determinant of resistance. Elderly people have a higher perception of risks compared to youngers. Specifically, mature segment resulted to be particularly concerned than youngers for the possibility of losing the list of PIN codes. Other risks like the case of third parties using their bank accounts or seeing their account information while using mobile banking services are not considered particularly high by both groups. This study evidenced that mobile banking security risks is perceived as lower even among non-users and the risk perceptions is higher for other types of risks during the service process, such as individual own errors, input and output mechanisms of a mobile phone, connection breaks or battery life. Even if tradition barrier did not result to be an obstacle to innovation adoption for both groups, younger people have a more positive perception of self-service alternatives in general. Similar findings were reported with regard to image barrier. Younger people resulted to have a more positive image of this service. However, even if mature customers did not consider new technology as too complicated to be useful, younger people have a slightly more positive perception (Laukkanen et al., 2007). With regard to gender, previous study evidenced the differences in customer behaviours among men and women. Indeed, gender is one of the most investigated customer demographics, especially in the electronic service context. Previous research suggested that men have a more positive attitude towards mobile commerce (Pijpers et al., 2001), have a lower perception of online business activities risk (Garbarino & Strahilevitz, 2004) and are more willing to adopt mobile banking services than women (Laukkanen & Pasanen, 2008, Garmarino & Strahilevitz, 2004). In line with previous research, Mani and Chouk (2018) research highlighted that women tend to resist more to smart bank services than men. These findings can be explained by psychology studies that reveal differences in decision-making and risk perception among men and women (Arch, 1993; Byrne & Worthy, 2015). Indeed, empirical studies noted that men are more willing to take risk then women and the use of smart services in the banking context is associated to a certain level of privacy and security risks (Mani & Chouk, 2018). Income often influence innovation adoption. Prior research has evidenced that lower income have a negative correlation with the usefulness perceived in the new technology, such as the Internet (Porter & Donthu, 2006) and with the adoption of electronic banking channels (Mann & Sahni, 2012). Laukkanen (2016) used Ram and Sheth (1989)'s theory in the Internet and mobile banking context to examine the different influence the five barriers and demographic variables (age, gender and income) have on customer rejection decisions. He found the central role of age and gender, while income resulted not to be determinant. Specifically, women resulted to be less likely to adopt mobile banking then men and mature segment resulted to be less likely to adopt mobile banking and have a lower level of intent to use internet banking than youngers.

2.5 Contribution of the research

According to Ram (1987) innovation adoption and resistance are not opposite of each other, "*they can coexist during the life of an innovation and can be explained by similar factors*. *Adoption begins only after the initial resistance offered by the customers is overcome"* (p. 208). A strong disagreement emerges from the literature review regarding the factors that lead individuals to take one of the two decisions (Gatignon & Robertson, 1989). While some authors have argued that resistance and adoption factors may even overlap and can be perceived as mere opposite in individual's mind (Day & Herbig, 2992), several research provided evidence that the reasons to adopt and to resist innovation are qualitatively different and they impact on decisions differently (Antioco & Kleijnen, 2010; Garcia et al., 2007). Therefore, the reasons to resist innovations are not necessarily the opposite of the reasons to adopt. Consequently, the literature on resistance goes on a different direction from the one on innovation adoption by proposing new theoretical models to investigate the factors of resistance.

Therefore, in light of this divergence of opinions, given the importance for firms to identify these factors since they have significant marketing implications (Kleijnen et al., 2009), this research aims at providing a greater clarity on the nature of the factors of adoption and resistance towards the Internet of Things (IoT) innovations. Specifically, the main contribution of this study is to examine customers' reasons to adopt and to reject smart services and smart objects and to identify, quantify and classify customers' emotions towards such AI embedded innovations. The investigation will be conducted through a Sentiment Analysis, also called Opinion Mining, discussed in Section 3.9, and a Content Analysis, discussed in Section 3.10, on a dataset, presented in Section 3.6, collected by applying the Critical Incident Technique (CIT), illustrated in Section 3.5.

More details about the methodology, the techniques used, the analysis and the results are discussed in the following chapter.

Chapter III

Methodology

Nowadays, millions of data are generated every minute, driven by the increasing number of users that can access the Internet all over that world and by the advances of the Internet of Things (IoT). On the basis of how they are organized, data can be classified in three different categories: structured, semi-structured and unstructured. However, in the recent years, with the development of Big Data, most of data collected are unstructured. Specifically, almost the 80% of the data generated globally is in unstructured text. It is widely recognized that meaningful and valuable customer insights can be extracted from an accurate analysis of these data. Therefore, companies able to organize, analyse and extract relevant information from their database can achieve a significant competitive advantage. The use of traditional techniques on unstructured databases could be time consuming, expensive and highly demanding in terms of work required. To overcome these issues, text mining techniques represent an efficient tool to automatically process a large amount of unstructured, natural language text, extract high quality and accurate information and find interesting patterns to support strategic decision making. Text mining definitions, features, advantages, activities required, and applications are discussed in Section 3.1. It is by using text mining that organizations can go deeper and analyse vast amount of contents in order to understand what customers think and feel about them and their products. This activity has become particularly necessary over the past two decades driven by advent of Internet and social media that have changed the way individuals interact and communicate. People feel free to express and share their thoughts, ideas, emotions and evaluations on multiple social media platforms, This huge volume of user generated content on the web makes easier for individuals to rely on this publicly available information about a product, a service, an individual or a business. Therefore, for companies it is critical to monitor the web on a continuous basis. Understanding and classifying opinions brings considerable benefits in almost every domain. For this purpose, sentiment analysis, discussed in Section 3.2, is one of the most used text mining technique. However, all of this could not be possible without the application of Machine Learning and Natural Language Processing (NLP), two of the major subfields of Artificial Intelligence (AI) that refers to the ability of machines to learn from experience, optimize their performance by adjusting to new input on a continuous basis and simulate human intelligence by thinking and acting like humans to increase the possibilities to achieve the desired goal. These concepts are presented in more details in Section 3.3. However, it is critical to emphasize that, despite the rapid development of sentiment analysis, multiples are the challenges that this field have to face to make the analysis as much accurate as possible. Some of the most relevant limitations of this technique are illustrated in Section 3.4.

After having introduced the theoretical tools to understand the concepts of text mining, sentiment analysis, artificial intelligence (AI), machine learning and natural language processing (NLP), the chapter continues by illustrating the Critical Incident Technique (CIT). Specifically, in Section 3.5, the CIT definitions, applications, advantages and disadvantages are discussed with the aim to understand this methodology as it has been applied in this study to collect textual data through interviews with the research objective to investigate and gain understanding of the Internet of Things (IoT) phenomenon, specifically customers' reasons to adopt and reject any IoT innovation and the polarity and polarity intensity of the emotions expressed. As seen in Section 3.6, these narrative data have been then organized in a dataset composed of 10 information categories (variables) and 156 interviews (86 negatives and 70 positives). In section 3.7, the collection of interviews was first converted into a corpus that was pre-processed and transformed in a WorldCloud and then in a "Bag of Words" matrix. In this contingency table, the first entry represents the list of terms, also known as the vocabulary of all the unique words that appear in the entire collection, while the second input corresponds to the interview number and each matrix value (cell) indicates the frequency of occurrence of the specific term in the interview. The frequency value of each word was then used as a feature to implement, in section 3.8, the Topic Modeling, a method of unsupervised machine learning, aimed at discovering natural groups of items and identifying distributions embedded in the set of available data. In Section 3.9 the sentiment analysis is performed on the textual dataset of 156 interviews. Specifically, in Section 3.9.1, the contingency table built in Section 3.7 was converted in order to extract, using the tools offered by the tidytext package, the *sentword* within the overall corpus text in order to have a first indicative measure of the polarity of the collection. By using the bing lexicon, sentiment words were identified and categorized as positive or negative. After having classified the sentiment words and identified their relative frequency, the focus of Section 3.9.2 is on measuring the polarity intensity and classifying the sentiment, by assigning a score to each interview through specific functions of the syuzhet package. It enables to extracts the sentiment from the text by using different sentiment lexicon dictionaries based on single words. Three sentiment lexicons were used in this study, namely "afinn", "bing" and "nrc". In the last Section 3.10, the content analysis is conducted on the interviews in order to investigate and identify inductively the most discussed reasons to resist and to adopt any kind of AI innovation. The interesting results emerged are illustrated in the Section 3.10.1 and Section 3.10.2, in which are discussed respectively the reasons for IoT innovation resistance and the reasons for IoT innovation adoption.

3.1 Text Mining

Every minute, millions of data are generated at a pace that seems not slowing down, driven by the increasing number of users that can access the Internet all over that world and by the development of the Internet of Things (IoT). Data can be classified in three different categories, defined on the basis of how they are organized, which are namely as structured, semi-structured and unstructured data. Before proceeding with the discussion, it is necessary to describe the main differences between these three types of data. Structured data, considered as the most "traditional" format, refers to any data that is highly-organized and formatted in a structure and that depends on a specific data model (a model that specifies how data should be store, processed and accessed).[19] Generally, these data are recorded in relational databases with a methodology of rows and columns that can easily and efficiently be processed and understood by machine (Aramburu et al., 2008). Structured data are managed with the SQL (*Structured Query Language*) programming language, which is particularly useful for handling relationships in databases. Common examples include names, dates, addresses, credit card numbers, geolocation and more.[20] Semi-structured data is a particular type of structured data and, as such, it contains tags and other markets to separate semantic elements, enforce hierarchies of records and fields within the data, but it does not conform with a formal structure, since it is not organized in relational databases. Blogs, Wikis, Forums, Tweets, Instant Messages are examples. (Monica & Ramesh Kumar, 2013) Lastly, unstructured data are not organized in a predefined format and do not depend on a defined data model. Therefore, data are organized in non-relational databases. The content of unstructured information, typically text-heavy with dates, numbers and facts, is complex to be analysed with conventional tools and methods due to irregularities and ambiguities. Common examples include audio, video files, word documents, email, PDF, graphics and multimedia.[21] In the recent years, with the development of Big Data, most of data collected are unstructured. Specifically, almost the 80% of the data collected globally is in unstructured text, and this number will continue growing driven by the exponential development of the Internet of Things (IoT) (Vallikannu et al., 2013). Text data (keywords, concepts, verbs, nouns, adjectives, etc.) can be sourced from chats, SMS, emails, newspaper articles, journals, customer feedback and reviews, tweets, and so on (Vishal & Guruprit, 2009). Companies have recently realized that the value that can be extracted from these unstructured text databases is an important source of competitive advantage. Of course, structured data provides useful insights, but the unstructured one contributes to a deeper

[19] BigDataFramework.com (2019). *Data Types: Structured vs. Unstructured Data*. Available at: https://www.bigdataframework.org/data-types-structured-vs-unstructured-data/ [accessed 28/03/2020].
[20] Pickell, D. (2018). *Structured vs Unstructured Data – What's the Difference?*. Available at: https://learn.g2.com/structured-vs-unstructured-data [accessed 28/03/2020].
[21] Ibidem.

understanding of customers' behaviour and thought. Companies could, indeed, gain knowledge about buying habits and timing, pattern in purchases, sentiment toward a product and much more.[22] Therefore, being able to organize, analyse and extract valuable information from raw data is one of the major challenge for many businesses.[23] However, the use of traditional techniques on unstructured databases could be time consuming, expensive and highly demanding in terms of work required, since unstructured text cannot be easily read by machines and used for more processing. As a consequence, important information could be only partially used or even completely ignored.[24] For these reasons, a new field that tries to extract meaningful information from natural language text has recently emerged. It is the so-called *Text Mining* (Vidya & Aghila, 2010). Text mining is defined by Oxford Dictionary as *"the automated process by which large volumes of unstructured, natural-language text are analysed in order to pinpoint and extract user-specified information."*[25] Similarly, Treccani Dictionary (2013) defines it as "*the dynamic acquisition of new knowledge regarding a certain domain through the application of data mining and information retrieval techniques applied on unstructured texts such as web pages, press agencies, e-mail and so on, and more generally to any document."*[26] Therefore, companies, by applying text mining techniques on unstructured textual data, can extract high quality and accurate information and find interesting patterns to support strategic decision making.[27] With text mining, the time required to process and analyse large volume of unstructured text data is reduced. Real time data monitoring enables companies to take rapid and timely business decisions to avoid potential negative consequences or to capitalize on opportunities as they emerge. The human error is completely avoided and the analysis leads to more consistent and objective results.[28] The large field of text mining embrace multiple disciplines concerning retrieval of information, analysis of text, extraction of information, categorization, clustering, visualization, mining of data and machine learning (Vishal & Guruprit, 2009). It is important to specify that text mining is not the first technique developed to analyse data. Indeed, until recently, data mining was the most common practice employed by many companies to monitor and analyse their structured datasets (Kumar & Bhatia, 2013). Data mining is defined by the Oxford Dictionary as "*the processing of large amounts of data in order to extract new kinds of useful information from it, based on patterns*

[22] Pickell, D. (2018). *Structured vs Unstructured Data – What's the Difference?*. Available at: https://learn.g2.com/structured-vs-unstructured-data [accessed 28/03/2020].
[23] BigDataFramework.com (2019). *Data Types: Structured vs. Unstructured Data*. Available at: https://www.bigdataframework.org/data-types-structured-vs-unstructured-data/ [accessed 28/03/2020].
[24] Expert System (2017). *Text mining and analytics: how does it work?*. Available at: https://expertsystem.com/text-mining-analytics-work/, [accessed 18/03/2020].
[25] Oxford Reference (2018). *Text Mining.* Available at: http://www.oxfordreference.com/view/10.1093/oi/authority.20110803103357444 [accessed 28/03/2020].
[26] Treccani (2013). *Text Mining*. Available at: http://www.treccani.it/enciclopedia/text-mining_(Lessico-del-XXI-Secolo)/ [accessed: 28/03/13].
[27] Expert System (2017). *Text mining and analytics: how does it work?*. Available at: https://expertsystem.com/text-mining-analytics-work/, [accessed 18/03/2020].
[28] Monkeylearn.com: https://monkeylearn.com/text-mining/ [accessed 30/03/2020].

and relationships."[29] It is a set of techniques based on algorithms and applied on structured data.[30] Text mining can be considered as a branch of data mining. They have the same analytical goal: discover valuable knowledge from data. However, despite apparently similar, they have meaningful differences in terms of the type of data they handle, the deployment time required and the way they approach analytics. Data mining deals with structured data, considered as homogeneous and universal. Once analysed, these data can be presented in different forms that can be easily read and processed by machines and humans and do not require any understanding of the context.[31] Text mining, instead, deals with unstructured text data that are presented as heterogeneous document format enriched with abbreviations and slangs. For what concern the deployment time, the easy accessibility of structured data makes data mining solutions quick to be provided once the algorithms are defined. On the contrary, the complexity of unstructured text data requires more linguistic stages of analysis before obtaining the results and this makes the process longer.[32] Moreover, when transforming data into valuable knowledge, data mining and text mining both use a broad variety of methods and technologies. Data mining applies directly to structured data multiple disciplines like statistics, artificial intelligence and machine learning in order to create models that enable descriptive, predictive and prescriptive analytics. Text mining, instead, deals with unstructured text data that need to be first organized before implement any data modelling or analytic function. Therefore, it requires the extra step of applying a series of sophisticated statistical and linguistic techniques on textual data. This process is enabled by Natural Language Processing (NLP), an Artificial Intelligence (AI) technique used to understand the meaning of natural human language. The Natural Language Processing (NLP) is discussed in more details in Section 3.3. Hence, text mining and data mining can be considered as two complementary practices. For example, data mining enables organizations predict future sales or patterns of demand. But it is by using text mining that organizations can go deeper and analyse vast amount of contents in order to understand what customers think and feel about them and their products. For this purpose, sentiment analysis, discussed in Section 3.2, is one of the most employed technique. It enables organizations to detect customer opinions and sentiments towards any entity by monitoring and analysing text data.[33] Text mining has the following four main features: cleaning, in categorization, extraction and modelling. *Cleaning* consists in organizing data, usually presented in unusual formats, for subsequent analysis. Once data have been organized, the *in-*

[29] Oxford Reference. *Data Mining*. Available at: https://www.oxfordreference.com/search?q=data+mining&searchBtn=Search&isQuickSearch=true [accessed 28/03/2020].
[30] Expert System (2016). *Text Mining Vs. Data Mining*. Available at: https://expertsystem.com/text-mining-vs-data-mining/ [accessed 28/03/2020].
[31] Ibidem.
[32] Ibidem.
[33] Opentext (2019). *What's the difference between data mining and text mining?*. Available at: https://blogs.opentext.com/whats-the-difference-between-data-mining-and-text-mining/, [accessed 28/03/2020].

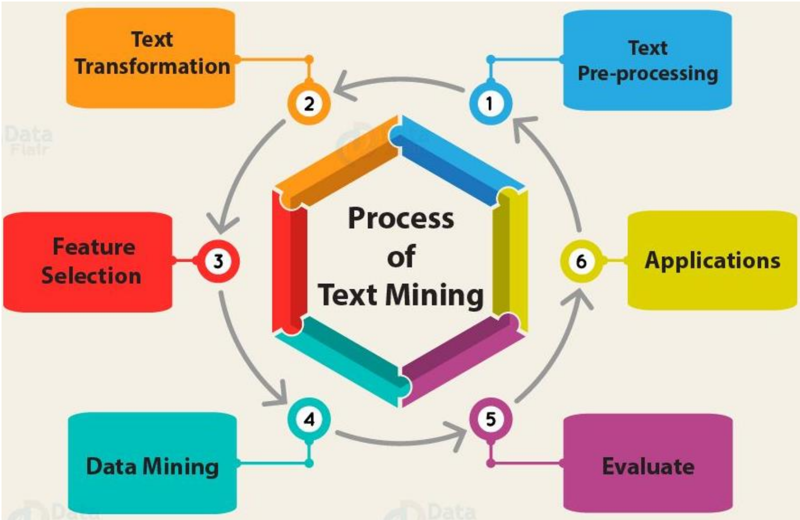
categorization feature enables a mechanical classification of the text in different categories. If the category is predefined, then it is possible to apply supervised machine learning algorithms; on the contrary, unsupervised machine learning techniques are required for text classification. *Extraction* deals with extracting valuable knowledge and information from the text. It first requires selecting the words and phrases that better identify the nature of the text. Lastly, *modelling* deals with combining the most important components of the text with more structured data attributes generally used in data mining. The purpose of this union is to optimize the forecast or simply to provide more detailed analysis results (Koslowsky, 2010).

Text mining process involves the following activities to be performed (Kumar & Bahria, 2013):

1. *Text Pre-processing:* it is made up of three different steps. The first one is Text Cleanup, which consists in removing all the unnecessary or unwanted data. The second one is Tokenization, which consists in splitting the text into white spaces. And lastly, Part of Speech Tagging, which consists in assigning a word class to each token.
2. *Text Transformation (Attribute generation):* it consists in representing a document text on the basis of the words (features) and their occurrences. It can be represented in two different ways based on Bag of words and Vector space.
3. *Feature Selection (Attribute Selection):* also known as *variable selections*, this technique is a subset of the general feature extraction field. It consists in selecting a subset of essential features to create a model. When selecting features, it is critical to take into account that the text document may contain many redundant or irrelevant features.
4. *Data Mining:* at this point in the process, the database has become structured and it can be analysed by applying data mining techniques.
5. *Evaluate:* it consists in evaluating the results obtained from the previous steps. Results can be discarded or used as input for other processes.
6. *Applications:* this last step consists in applying text mining results. This technique influences greatly a lot of industries all over the world. The most common applications are Web Mining, that aims at discovering valuable hidden patterns from the Web, Medical, that aims at helping medical experts to automatically categorize visitors ‘requests, Resume Filtering, that aims at helping big companies to automatically select or discard between a myriad of job applications and resumes, Social Media Analysis, that aims at analysing the text content on social media for multiple purposes, and much more (Anand Babu & Srinivasu, 2019).

Fig. 3.1 summarizes the above described text mining process.

Fig. 3.1. Text Mining Process



Source: DataFlair, 2018

In conclusion, nowadays, text mining and data mining are both considered beneficial techniques for an optimal and efficient business management in every industry. Given the rapid increase of unstructured text data, driven by the digitalization, the development of social networks and the proliferation of user-generated contents on the web, the application of text mining technique is essential. Specifically, monitoring individual customers' opinion, sentiment, attitude and thought online has become a critical new target for many businesses. For this purpose, opinion mining (sentiment analysis) is the most common technique applied.

3.2 Opinion Mining (Sentiment Analysis)

Opinions are critical in influencing almost every behaviour and decision. The choice we make, our beliefs, the perception we have are all strongly influenced by the way other people see and evaluate the world. This is true for both individuals and organizations. For example, individual customers rely a lot on other people's reviews about a product or service before purchasing it, thus businesses need to collect public or customers' opinion to monitor the perception people have about them. In the past, individuals had to ask for opinions to family or friends, while companies had to conduct expensive and time-consuming opinion polls, surveys, and focus groups (Liu, 2012). However, over the past two decades, the advent of Internet and social media has changed the way individuals interact and communicate (Qualman, 2010). Nowadays, people feel free to express and share their thoughts, ideas, emotions and evaluations on multiple social media platforms, like forum discussions, blogs, twitter, review sites and much more in a very simple way. The huge volume of user generated content on the web makes easier for individuals to rely on this publicly available information about a product, a service, an individual or a business (Varathan et al.,2017) rather than ask relatives or friends.

Brightlocal's online review survey reveals that the 88% of customers trust online reviews and rely on them when making their purchase decisions. Therefore, for companies it is critical to monitor the web on a continuous basis, since it would provide useful insights to make strategic business decisions, identify potential risks and emerging opportunities and manage the online reputation (Varathan et al.,2017). However, extracting and summarizing relevant and valuable information from the myriad of contents published on multiple platforms may be extremely demanding for an average human reader. For this reason, an automated sentiment analysis (opinion mining) is needed (Liu, 2012).

Opinion mining, also called sentiment analysis, is a type of natural language processing, defined as the area of study that focuses on developing methods that can automatically detects, extracts and analyses sentiments, emotions, opinions, evaluations, attitudes and appraisal about an "opinion target", like a product, a service, a business, an individual, an event, an issue, a topic and much more expressed in digital forms on social media platforms (Liu, 2012; Vinodhini & Chandrasekaran, 2012; Varathan et al., 2017). Linguistics and natural language processing (NLP) have a long history. There are a lot of studies about the interpretation of metaphors, sentiment adjectives, view points and affects. However, the sentiment analysis research has grown exponentially since the early 2000 driven by the technological advances and the development of social media, in which a huge volume of opinion data text are easily accessible (Liu, 2012). Before proceeding with the discussion, it is critical to formally define what is an opinion. Liu (2012, p. 26) defines it as *a "subjective statement, view, attitude, emotion, or appraisal about an entity or an aspect of an entity from an opinion holder. The entity is a concrete or abstract object such as product, person, event, organization which can be represented as a hierarchy of components, sub-components, and their attributes".* Sentiment analysis metrics are used to categorize text according to the following criteria: the polarity of the sentiment expressed through the opinion (positive, neutral or negative), the polarity of the outcome, the level of agreement with a topic, whether the news is good or bad, support or opposition attitudes and, lastly, pros or cons opinions (D'Andrea et al., 2015).

Sentiment analysis focuses on the following three main field of research (Vinodhini & Chandrasekaran, 2012):

- *Sentiment classification:* entire documents are classified according to the opinions expressed in it towards a certain entity.
- *Feature based sentiment classification:* takes into account opinions about the features of a certain entity.
- *Opinion summarization:* takes into account only the features of the product on which customers have expressed their opinions.

Sentiment analysis investigates mainly three different classification levels (Liu, 2012):

- *Document level:* it consists in identifying the overall opinion polarity of an entire document toward one single entity. Therefore, this level of classification cannot be applied on documents that evaluate or compare multiple entities.
- *Sentence level:* it consists in identifying the opinion polarity of each sentence. It requires to distinguish between objective sentences, containing factual information, and subjective sentences, which contains subjective views. The latter are then analysed to be classified.
- *Entity and aspect level:* also known as *feature level*, it is the finest level of analysis. It focuses on the opinion itself, composed by a sentiment (positive or negative) and a target (entity) of opinion, and aims at discovering sentiments on entities and/or their specific multiple aspects mentioned in each sentence.

Understanding and classifying opinions brings considerable benefits in almost every domain. Government intelligence and business intelligence are two major applications. The government uses opinion mining to detect what citizens think and want in order to act on it and to predict voter's preferences and election results. Companies can instead detect customer's satisfaction level about their products and services (Varathan et al.,2017), predict sales performance, rank products, find gender differences, predict the stock market, study trading strategies and much more (Liu, 2012). Opinion mining practices are also particularly beneficial in the field of competitive intelligence and marketing. Businesses can extract and visualize comparative relations between products by analysing customers' review and measure the effectiveness of their campaigns or product launches (D'Andrea et al., 2015), observe their performance on the market, detect potential risks or emerging opportunities (Vinodhinui & Chandrasekaran, 2012), predict and manage the customer retention rate, predict customer trends and much more.[34] Sentiment analysis applied on social media monitoring can be used for reputation management (or brand monitoring) activities aimed at keeping track of a company or brand reputation on different social media platforms in order to act promptly in case of need and avoid that customers could switch to competitors. Sentiment analysis is also applied to monitor competitors. By keeping track of competitors 'performance, a company could have a benchmark metric to compare with.[35] The insights obtained can be used to adjust the business strategy accordingly and gain a

[34] Gupta, S. (2018). *Applications of Sentiment Analysis in Business*. Towardsdatascience. Available at: https://towardsdatascience.com/applications-of-sentiment-analysis-in-business-b7e660e3de69 [accessed 29/03/2020].

[35] Rogalski, K. (2018). *What are the applications of sentiment analysis? Why is it in so much discussion and demand?*. Quora. Available at: https://www.quora.com/What-are-the-applications-of-sentiment-analysis-Why-is-it-in-so-much-discussion-and-demand [accessed 29/03/20].

competitive advantage by increasing customer satisfaction and enhancing customer experience that both have a positive impact on customer loyalty, capitalizing on opportunities and avoiding threats.[36]

It is worth emphasizing that all of this could not be possible without the application of Natural Language Processing (NLP), a branch of artificial intelligence focused on the analyses of natural human language that is discussed in more details in the Section 3.3.

3.3 Artificial Intelligence (AI): Machine Learning and Natural Language Processing (NLP)

In the latest years, the exponential increase in the amount of data volumes, the developments of advanced algorithms and the improvements in computing power and storage have driven the growth of Artificial Intelligence. The term has its roots in 1956 and it was first used during the *Dartmouth Conference* to identify the field of study focused on training computers to mimic basic human reasoning. Over the last decade, Artificial Intelligence (AI) research has evolved significantly providing a myriad of benefits in every industry (health care, manufacturing, banking, retail and much more). Formally, Artificial Intelligence (AI) refers to the ability of machines to learn from experience, optimize their performance by adjusting to new input on a continuous basis and simulate human intelligence by thinking and acting like humans to increase the possibilities to achieve the desired goal. Machines should be able to execute any kind of task, from the simplest to the most complex. These include planning, decision-making, perceiving, reasoning and acting, language understanding, object and sound recognition, learning and problem solving. By using an iterative processing and intelligent algorithms, Artificial Intelligence (AI) is able to analyse huge amount of data and find patterns or features that are then used by the software to optimize its performance (SAS, 2019).

Artificial Intelligence (AI) is a broad area or research that includes multiple theories, technologies, methods and subfields. For the purpose of this work, among the major subfields, it is critical to mention and describe two of them, namely Machine Learning and Natural Language Processing (NLP) (SAS, 2019). The term Machine Learning was first coined in 1959 by Arthur Samuel, who defined it as "*the field of study that provides computers the ability to learn without being explicitly programmed*" (Das, 2017). Subsequently, Tom Mitchel (1997) provided a more modern definition: "*a computer program is said to learn from experience E with respect to some class of tasks T and performance measure P, if its performance at tasks in T, as measured by P, improves with experience E."* Therefore, machine learning enables computers improve their performance and minimize errors

[36] Gupta, S. (2018). *Applications of Sentiment Analysis in Business*. Towardsdatascience. Available at: https://towardsdatascience.com/applications-of-sentiment-analysis-in-business-b7e660e3de69 [accessed 29/03/2020].

by adjusting and optimizing the algorithms in an iterative manner based on the data provided by previous experiences (Pressi, 2019). Accordingly, the most important aspect for an effective functioning of the machine learning process is repetitiveness: the more the model is exposed to data, the better it is able to adapt autonomously, produce results and make decisions that are reliable and replicable in the future (SAS, 2018). Machine learning automates the construction of analytical models. It uses neural network methods, statistical models and operational searches to find information hidden in the data. A neural network is a type of machine learning inspired by the functioning of the human brain. It is a computational system consisting of interconnected units, similar to neurons, that process information by responding to external inputs and transmitting the related information between different units (Di Paolo Emilio, 2018).

There are three main machine learning approaches[37][38]:

1. *Supervised machine learning:* it consists in training a machine while having access to a full set of labelled data in the "training" dataset. Therefore, the algorithm learns from labelled data. Each data is tagged with the result that should be provided autonomously by the algorithm. During the training phase, the machine can access to examples of correct input and output pairs. Supervised learning is best suited when there is a set of reliable available reference examples to learn from. This approach is particularly useful in two main areas: classification problems, which consists in assigning observations in discrete class, and regression problems, which consists in estimating a continuous quantity.
2. *Unsupervised machine learning:* it consists in a training dataset which contains data without a specific outcome or correct answer, because it may be unobservable or infeasible to obtain. Thus, it is required a neural network that analyse the dataset to find automatically a structure, extract meaningful features and patterns. The structure that the unsupervised machine learning produces within the dataset depends on the problem at hand. An application of this approach is clustering, which deals with classifying observations in different categories in which members of the same groups are similar to each other and different from those of other groups.
3. *Reinforcement machine learning:* it is an iterative process that resembles the way humans and animals learn. It is based on the assumption that as the agent tries to take steps to reach

[37] BrainStation (2017). *Machine Learning 101 | Supervised, Unsupervised, Reinforcement & Beyond*. Towardsdatascience. Available at: https://towardsdatascience.com/machine-learning-101-supervised-unsupervised-reinforcement-beyond-f18e722069bc [accessed 01/04/2020].

[38] Salian, I. (2018). *What's the Difference Between Supervised, Unsupervised, Semi-Supervised and Reinforcement Learning?*. Available at: https://blogs.nvidia.com/blog/2018/08/02/supervised-unsupervised-learning/ [accessed 01/04/2020].

a particular goal, it receives rewards or punishments. The agent learns from these feedbacks and, to make decisions, relies both on them and on possible new tactics that may lead to a larger payoff. The more feedbacks the agent receives, the better it can make the next decision. The overall objective is to predict the best next action to take. This approach is particularly useful if the machine can be programmed to act as an agent that is able to interact with its surrounding environment and the solutions are multiple or even infinite.

The particular machine learning area focused on the analyses of written text is known as Natural Language Processing (NLP). This science is not new. However, the related technologies have improved over the last decade due to continuous research in human-to-machine communications, a greater availability of Big Data, advanced algorithms and computing power. [39] Furthermore, in recent years, with the development of the mobile internet phenomenon and the emergence of new social media, the use of the written language has grown exponentially. Today we have access to a huge amount of user generated data encoded in natural language that are produced on a continuous basis on a myriad of platforms on the Web. Natural language is the language we use in everyday life, such as English, Russian, Japanese, Chinese, and it is synonymous with human language, mainly to distinguish it from other languages, such as computer language. Human language is quite complex and may differ from an individual to another, since there are hundreds of languages, dialects, set of grammar and syntax rules, terms and slangs. In addition, in written text people may abbreviate words, misspell or omit punctuation.[40] For this reason, this form of automation has become essential to analyse efficiently, rapidly and in an unbiased manner text-based data (Celi, 2018).

Natural Language Processing (NLP) can be formally defined as "*a branch of artificial intelligence that helps computers understand, interpret and manipulate human language. NLP draws from many disciplines, including computer science and computational linguistics, in its pursuit to fill the gap between human communication and computer understanding.*"[41] This is one of the most important methodology employed by text mining to transform unstructured text contained in documents and databases into a more structured form that can be integrated in data warehouses, business intelligence dashboards or databases to run descriptive, prescriptive or predictive analysis.[42] Natural Language Processing (NLP) includes both *Natural Language Understanding*, that simulates

[39] SAS (2019). *Natural Language Processing (NLP): What it is and why it matters*. Available at: https://www.sas.com/en_us/insights/analytics/what-is-natural-language-processing-nlp.html [accessed 01/04/2020].
[40] Ibidem.
[41] Ibidem.
[42] Linguamatics (2018). *What is Text Mining, Text Analytics and Natural Language Processing?,*. Available at: https://www.linguamatics.com/what-text-mining-text-analytics-and-natural-language-processing [accessed 01/04/2020].

the human ability to understand natural language and, thus, read text, hear speech, and measure sentiments, and *Natural Language Generation*, that simulates the human ability to create natural language text, but also to answer questions on different topics and to perform complex tasks. Virtual Assistants like Siri by Apple and Alexa by Amazon are two applications of this technology.[43]

In Natural Language Processing (NLP), it is meaningful to distinguish two different level of analysis [44][45]:

- *Syntactic level:* it focuses on the analysis of words in order to identify the grammar and the structure of each sentence. It is based on the assumption that in most languages the meaning of a sentence depends on the word order and dependency.
- *Semantic level:* it focuses on understanding the meaning of words on an individual level by taking into account the context of words in each sentence. Therefore, it determines the possible meaning of a sentence, focusing on the interactions between the words it contains. This level aims at determining what a sentence really means by relating syntactic features and disambiguating words, that have multiple meaning, to the context. Several methods can be implemented to perform the disambiguation. Some require information about the word frequency in a particular corpus of interest, some require consideration of the local context, and others use pragmatic knowledge of the document domain.

Natural Language Processing (NLP) may employ a variety of approaches to analyse and process natural human language. The *symbolic approach* deals with recording generally accepted grammar rules and lexicons of a specific language in computer systems. These rules are then used for the analyses. The *statistical approach*, by using mathematical analysis of large document text, can detect recurring themes and trends of linguistic phenomena in large text sample in order to develop its own linguistic rules that will be used to analyse or generate text in the future. Lastly, the *connectionist approach* connects the previous two approaches described. Indeed, it combines generally accepted linguistic rules with inputs obtained from statistical inferences.[46] Nowadays, NLP-based technologies are becoming more and more widespread and the applications are creating substantial value in a myriad of sectors and industries. These technologies are present almost everywhere, helping us

[43] Linguamatics (2018). *What is Text Mining, Text Analytics and Natural Language Processing?.* Available at: https://www.linguamatics.com/what-text-mining-text-analytics-and-natural-language-processing [accessed 01/04/2020].

[44] Expert System (2016). *What is Natural Language Processing?.* Available at: https://expertsystem.com/natural-language-processing/ [accessed 01/04/2020].

[45] *Appuntisoftware.it:* https://www.appuntisoftware.it/metodologie-e-tecniche-del-natural-language-processing/TI [accessed 01/04/2020].

[46] Expert System (2016). *What is Natural Language Processing?.* Available at: https://expertsystem.com/natural-language-processing/ [accessed 01/04/2020].

performing everyday activities, even if we may not be able to realize it. Machine translation, automatic summarization, text classification and question answering are among the most widely used applications. Machine translation deals with helping users overcome language barriers by translating texts. Automatic summarization deals with helping users overcome the problem of information overload by enabling them to access the specific information they are looking for among a huge knowledge base. It is useful to summarize text documents and to understand the emotional meaning contained in it. Text classification enables to organize information in a document and, thus, it helps the user find what he needs. Spam filtering is an example. Question answering enables the human-machine communication by creating a system that, through an interactive interface, is able to answer human requests in a written or spoken manner. Virtual assistants are an application of this technology.[47] From the business point of view, Natural Language Processing (NLP) is a huge source of value. Nowadays, regardless of the sectors almost every firm have to deal with a huge amount of Big Data, most of which are expressed in natural language text. Natural Language Processing (NLP) simplifies and makes the analysis more rapid and accurate.[48] It also represents a huge opportunity to identify patterns, trends, relevant information and valuable insights that can be exploited to optimize processes, improve customer experience, increase satisfaction and engagement.[49] Natural Language Processing (NLP) is the practice that makes the sentiment analysis possible. It enables to understand the language used and discover the true sentiment and attitude behind it. It is extremely useful for businesses, since Natural Language Processing (NLP) makes social media monitoring activities easier and enable companies to discover and collect valuable insights about their customers, competitors and the market, to make the best business decisions and adjust their strategies accordingly to achieve a competitive advantage. [50]

3.4 Opinion mining: *Challenges*

Sentiment analysis (or opinion mining) is a field in rapid development. Over the past decade, there has been a lot of research about it and it continues to progress in new directions. However, this dynamism together with the complex and multiple forms in which opinions can be expressed lead to numerous challenges that may become huge obstacles for an accurate analysis. Authenticity and

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[47] Expert System (2016). *Natural language processing applications*. Available at: https://expertsystem.com/natural-language-processing-applications/ [accessed 01/04/2020].

[48] Expert System (2017). *Natural Language Processing Introduction*. Available at: https://expertsystem.com/natural-language-processing-introduction/ [accessed 01/04/2020].

[49] Expert System (2016). *NLP for Big Data: What everyone should know?*. Available at: https://expertsystem.com/nlp-big-data-everyone-know/ [accessed 01/04/2020].

[50] Expert System (2016). *Natural Language Processing for Sentiment Analysis*. Available at: https://expertsystem.com/natural-language-processing-sentiment-analysis/ [accessed 01/04/2020].

trustworthiness of the opinion are critical for an effective sentiment analysis to be implemented. The web contains a large amount of fake or spam contents as well as non- expert opinions, that should be detected and eliminated before the analysis. However, identifying believable and trustworthy opinions is not so easy, and, thus, it is one of the biggest challenge that opinion mining has to face (Khan et al., 2018). Furthermore, the human language is characterized by ambiguities, inferences and implicitness that make the sentiment analysis process quite difficult (Haseena Rahmath, 2014). The challenging aspect can be related to the double meaning of some words that may be considered positive in one situation and negative in an another, to typo errors, to the different ways in which people express their opinions, to the absence of an opinion context and to the continuous contradictions that make difficult even for other humans to understand someone's thought (Vinodhini & Chandrasekaran, 2012). Numerous are the word level challenges faced by sentiment analysis due to the use of sarcastic and ironic statement that erroneously orient opinions, the use of abbreviation and short forms, the use of orthographic words to express emotions, the use of context dependent words, that if expressed in different context can have two or more distinct meanings, the use of simile or metaphors, the use of synonym words, the use of negation words and the use of comparison words used in opposite meaning (Khan et al., 2018). At the sentence or language level, opinion mining has to deal with opinions expressed in different languages, different style writing from an individual to another, the use of the informal, casual and colloquial language, the used of multiple languages in one single opinion, the difference between the target topic opinion and the opinion expressed and much more (Khan et al., 2018). The opinion volatility can be considered another important challenge for opinion mining. Indeed, it may be a difficult task for a machine to detect the strength and polarity of an opinion, which may change during a discussion or with the passage of time as information unfolds (Khan et al., 2018). The analysis should also take into account the domain dependent nature of sentiment words. Indeed, one feature set may be suitable for one domain and not suitable at all for another one (Haseena Rahmath, 2014). Therefore, it is clear that despite the latest advances in the opinion mining field, there is still a lot to improve. All of the above-mentioned issues could be easily overcome by humans, since it is more simple for them to extract and interpret properly opinions from a given text. However, this "traditional" method is expensive, time consuming and results are subject to human error. For this reason, it is critical to keep on studying to optimize machines in order to address all of these challenges and make the sentiment analysis as much accurate as possible.

3.5 Critical Incident Technique (CIT)

The Critical Incident Technique (CIT) is an inductive grouping procedure (Hunt, 1983) introduced to the social science by Flanagan in 1954. It can be defined as a "*set of specifically defined procedures* *for collecting observations of human behaviour and classifying them in such a way as to make them useful in addressing practical problems"* (Bitner et al., 1990, p. 73). Chell and Pittaway (1998) provided a more detailed description defining it "*as a qualitative interview procedure which facilitates the investigation of significant occurrences (events, incidents, processes, or issues) identified by the respondent, the way they are managed, and the outcomes in terms of perceived effects. The objective is to gain understanding of the incident from the perspective of the individual, taking into account cognitive, affective, and behavioural elements*" (p. 56). Therefore, this method aims at collecting rich narrative information about a construct of interest in order to explore it and obtain useful insights about the frequency or the existence of patterns of factors within the phenomenon investigated and classify it in different categories (Woolsey, 1986). The latter can be either identified from an inductive interpretation of data or can be deduced from theoretical models (Strauss and Hentschel, 1992). Data can be collected in multiple ways, such as observations, interviews or focus groups (Flanagan, 1954). The CIT is a reliable method to collect information from a large number of individuals (Grove and Fisk, 1992) to conduct research aimed at investigating a phenomenon about which there is little knowledge available (Bitner et al., 1990) and for which it is difficult to specify in advance all the variables (de Ruyter et., 1995). Therefore, it needs no hypothesis and the researcher identifies concepts and theories as they emerge from the analysis (Olsen & Thomasson, 1992).

The main object of analysis of the CIT are behaviors or events that lead to success or failure when performing a given action or task, also known as "critical incidents" (Ronan & Latham, 1974). An "incident" is defined as "*an observable human activity that is complete enough in itself to permit inferences and predictions to be made about the person performing the act* (Bitner et al., 1990, p. 73). It is "critical" when *it contributes to or detracts from the general aim of the activity in a significant way"* (Bitner et al., 1990, p. 73). Therefore, not all incidents are critical, since they have to make a significant contribution to a given activity, either positively or negatively (Bitner et al., 1990).

Unlike other inductive grouping techniques (factor analysis or cluster analysis), the CIT employs a content analysis of stories, rather than quantitative solutions, to identify categories in a specific dataset. Content analysis "*takes the communication that people have produced and asks questions of the communications"* (Kerlinger, 1973, p. 525). Similarly, the CIT, by asking questions of the stories that people have told, classifies each of them within a scheme. Therefore, by using open-ended text narratives, the CIT collect narrative description of particularly relevant incident of satisfaction or dissatisfaction, enabling an exploratory study of the significant aspects of the topic of interest (Woolsey, 1986). Researchers can thus elicit and capture valuable information from the analysis (Swan & Rao, 1975). Content analysis on multiple forms of communications has been largely applied in different fields ranging from political science to education, social psychology, journalism and much more. It has recently found a relevant application in marketing with the aim to analyse the content of advertising (Pollay, 1985), comics (Belk, 1987; Spiggle, 1986) and retail store image (Zimmer & Golden, 1988). Similarly, the CIT, first used in the field of psychological research, has been applied in multiple disciplines (Butterfield et al., 2005): it was used to study service quality and failures (Bell et al., 1997; Longo et al., 1993), product quality (Archer & Wesolowsky, 1996; Swan & Combs, 1976) and organizational culture (Jordan, 1996; Mallak et al., 2003). The CIT does not force respondents or use strict directions. They are left free to decide which incident is the most significant in relation to the phenomenon of interest and to express what they really think in their own words and language (Strauss & Weinlich, 1997). For this reason, the CIT is particularly useful for marketers: it makes the decision-making processes clearer, enabling them to understand how their customers actually think (Nyquist & Booms, 1987). However, the focus should remain on individual's detailed story of the specific occurrences or behaviour that affected their evaluation of a specific event. The observations collected can be then categorized to identify the critical requirements of an activity (Flanagan, 1954). The CIT combines "rigor and vigor" by applying both qualitative and quantitative examination of communication and has the advantage to be able to interpret accurately and consistently people's stories of events maintaining their power and eloquence aspects (Viney, 1983). Although the CIT has a lot of benefits, this method has also received many critics. One of the main limit of this procedure is related to the reliability and validity of the categories extracted from the dataset due to the reliance on open-ended narrative text, the subjective judgement required for classification, the ambiguity of word meanings, category labels and coding rules in a particular study (Weber, 1985). It may result in a misinterpretation or misunderstanding of respondents'stories reported in incidents (Edvardsson, 1992). However, with regard to the general reliability and validity of the CIT, Andersson and Nilsson (1964) research evidenced that the data collected by using this procedure are both reliable and valid. In line with these findings, also Ronan and Latham (1974) and White and Locke (1981) studies conducted to the same results. Other issues may be related to recall bias (Michel, 2001), consistency factors or memory lapses (Singh and Wilkes, 1996) that could mistake the procedure. Indeed, the CIT is a retrospective method that relies on respondents 'memory and requires an accurate and truthful narration of the events that may have occurred some time before the collection of the data and respondents may tend to reinterpret it (Johnston, 1995). Another limitation is related to the possible low response rate, since this technique requires respondents to be willing to spend time and effort to provide detailed descriptions of what they consider to be critical incidents (Johnston, 1995).

Traditional manual analysis of critical incidents enables to classify them into iteratively and subjectively defined categories but may ignore their emotional content and emotional intensity (Van Dolen et al., 2001). Indeed, critics highlight the lack of a scale to assess the emotional impact of a response (Akerman et al., 2018). While it is easy to classify a text as positive or negative, the specific amount of satisfaction or dissatisfaction in the incident is subject to the evaluation of the reader (Akerman et al., 2018). The latter has to review and classify critical incidents and inductively develop categories and subcategories simply relying on own skills and sophistication (Flanagan, 1954). However, this task is particularly demanding, especially in case of large datasets (Akerman et al., 2018). Therefore, in business context, the CIT becomes particularly laborious since is involves the analysis of thousands of customer responses. The latest advances in artificial intelligence could be useful to overcome this issue. These advances in data process algorithms and in sentiment analysis tools are valuable substitute to manual coding critical incidents (Akerman et al., 2018) and enable to classify large sets of text into categories and assign to each response an emotional intensity numerical value. Akerman et al. (2018) proposed that the use of these data analytics algorithms can improve the quality and the effectiveness of CIT data analysis by reducing the time required to identify strongly-worded incidents, by identifying a relative scale of emotional intensity and by increasing the speed to code the emotional intensity of large data sets.

In this study, the CIT procedure was applied to collect narrative data through interviews with the research objective to investigate and gain understanding of the Internet of Things (IoT) phenomenon, specifically customers' reasons to adopt and reject any IoT innovation and the polarity and polarity intensity of the emotions expressed. The critical incident, or event, respondents had to describe was about a recent opportunity in which they had the possibility to purchase a product with built-in AI and/or to use a service with built-in AI but they did not purchase/use it or they eventually decided to purchase/use it. They were then asked what the product or service was, the reasons that led them not to buy/use or to buy/use a product or service and what they felt and thought during the episode. This enabled to obtain 156 interviews of which 86 describe episodes of innovation adoption and 70 describes episodes of innovation resistance. The textual data were organized in a dataset illustrated in Section 3.6. Subsequently, a sentiment analysis and a content analysis were then conducted on it respectively in Section 3.9 and Section 3.10.

3.6 Dataset

The data collected by applying the CIT technique were organized in a dataset that is presented in this section. It is composed of 10 information categories (variables), each of which correspond to a column, and 156 interviews, (86 negatives and 70 positives). As shown in Fig. 3.2, the variables are character class vectors (i.e. character codes that can be expressed as text strings).

Fig. 3.2. Data Set Variables

	Class
(1) Please, think of and describe a recent opportunity in which you had, and exploited, the possibility to purchase a product with built-in AI and/or to use a service with built-in AI.	Character
(2) What was the product or service?	Character
(3) When did the episode happen?	Character
(4) What are the reasons that led you to buy the product or use the service?	Character
(5) Exactly, what did you feel and think during the episode?	Character
(6) How many devices with built-in artificial intelligence do you own?	Character
(7) What types of devices with built-in artificial intelligence do you own?	Character
(8) How many services with built-in artificial intelligence do you use?	Character
(9) What types of services with built-in artificial intelligence do you use?	Character
(10) Gender	Character

The subsequent step was a data cleaning process: eight columns considered as not relevant for the research objective were discarded and the remaining two, respectively the column (1) and (5) of Fig. 3.2, were combined together. The resulting dataset is the focus of the subsequent analysis.

It is critical to specify that, for research purposes, the positive and negative interviews were combined together to perform the sentiment analysis, but they are kept separated to conduct the content analysis.

3.7 Bag of Words (WordCloud)

Generally, textual data are not organized in a predefined structure and this characteristic makes the analysis of such data quite complex. Techniques like machine learning algorithms do not work efficiently if applied directly to raw texts: a well-defined fixed-length inputs and outputs is needed. The text has to be converted into numbers (specifically, vectors of numbers) in order to enable the "feature extraction" or "feature encoding" process. Goldberg (2017), in his work *Neural Network Methods in Natural Language Processing,* states that *"in language processing, the vectors x are derived from textual data, in order to reflect various linguistic properties of the text"* (p. 65). One of the most simple and applied method to extract feature from text is the so-called *Bag of Words (BoW)* model. It can be defined as a textual representation and analysis that enables to extract specific features from text document. These features are first organized within a textual corpus and then within a two-dimensional matrix. In this study, each interview is transformed into a vector that can be used as an input (or output) for machine learning algorithms.[51] This is a two-step process:

1. Given n interviews, the binary scoring method is applied to the first one: the occurrence of a word is marked as a boolean value (0 if absent, 1 if present). In this way, the interview is converted into a score vector and the words that make it up represent the vocabulary in an early version.
2. The above mentioned vector transformation process is repeated for all interviews until the matrix is obtained. The latter has two entries. One corresponds to a list of term that represents the vocabulary of all the unique words that appear. The other entry points out the occurrence frequency of each term for each interview.

With the creation of the matrix the informational content of the text remains unaltered. However, the term "bag" indicates that the order and structure of the words in the text are discarded and lost since the model only focuses on whether and how many times a specific word is present in the document regardless of its position. Each word count is considered as a feature. As the size of the vocabulary increases, the vector representation of documents increases as well. Therefore, for a corpus composed by a collection of thousands of interviews, we would obtain a very long vector with thousands of positions. However, when each document contains very few words of the total vocabulary, it would result in a "sparse vector" or "sparse representation", which is a vector with a lot of zero scores. Sparse vectors require more computational resources and memory and when the total vocabulary is composed by many words the modelling process become complex for traditional algorithms. For this reason, when applying the BoW model, there is a strong pressure on reducing the size of the vocabulary.[52] The most common vocabulary reduction methods are (Traspinar, 2015):

- *Removal of punctuation and numeric characters*: despite punctuation and numbers are often good indicators of individual's sentiment, they tend fragmenting the tokens by cluttering up the classification pointlessly. For this reason, many tokenizers eliminate them: pre-processing is, indeed, an attempt to generalise the data by removing what is useless for research purposes.
- *Removal of stopwords*: stopwords are common usage words that must be removed in the pre-processing phase. These words, within a document, could be dominant in number of

[51] Browniee, J. (2017). *A Gentle Introduction to the Bag-of-Words Model.* In Deep Learning for Natural Language Processing. Available at: https://machinelearningmastery.com/gentle-introduction-bag-words-model/ [accessed 10/05/20]

[52] Browniee, J. (2017). *A Gentle Introduction to the Bag-of-Words Model.* In Deep Learning for Natural Language Processing. Available at: https://machinelearningmastery.com/gentle-introduction-bag-words-model/ [accessed 10/05/20]

occurrences but at the same time their information content is not relevant for the analysis. At the same time, there could be scarcer words that have a greater meaning.

- *Stemming process*: it is a pre-processing step whose aim is to reduce the inflectional forms and derivationally related forms of a word to a common base form in order to efficiently apply machine learning algorithms on textual data. For grammatical reasons, multiple forms of a single word can be used within a document (*organize, organizes* and *organizing* is an example). In addition, words can be grouped in derivationally related families of words (*democracy, democratic* and *democratization* is an example).[53] Therefore, with the stemming process, words are reduced to their "word stem", which is a word root that is not necessarily the dictionary-based morphological root. It is usually only necessary that the correlated words are mapped to the same root, even if this is not a valid root in itself. [54] Once the root of each word has been identified, it replaces the word itself within the text corpus. The algorithms used in this process are called "stemmers". This *Information Retrieval* method results in a text with the same number of terms but with fewer variants.

Generally, in order to reduce text complexity, stopwords are discarded before applying the stemming process. In this way, the stem words have to be found for a fewer number of words. This reduces the time of execution and increases the computational efficiency, thus simplifying the algorithm. In stemming, root reduction can occur with different degrees of stem. It is critical to take a balanced decision, otherwise two types of errors may arise, namely "over-stemming" and "under-stemming". Over-stemming occurs when too much of a word is removed. In this case the result is a large family of words many of which may have different meanings with a consequent loss of specificity. Under-stemming occurs when the stem chosen is long. Therefore, it would result in a family of very few words that are strongly related but the risk is that some words with the same meaning are discarded, with a consequent loss of generality (Porter, 2001). Stemming algorithms can be grouped within two main categories: rule-based and statistical. Rule-based algorithms require a high level of knowledge of the language. Common approaches are the use of word morphology, the application of rules to remove affixes and the detection of inflected or derived forms. Statistical algorithms are mostly applied to complex languages; they require to be trained from a corpus, a lexicon or a character-based

[53] Manning, C. D., Raghavan, P., Schütze, H. (2008). *Introduction to Information Retrieval*. Cambridge University Press. Available at: https://nlp.stanford.edu/IR-book/html/htmledition/stemming-and-lemmatization-1.html [accessed 10/05/20]

[54] Heidenreich, H. (2018). *Stemming? Lemmatization? What?***.** Towardsdatascience. Available at: https://towardsdatascience.com/stemming-lemmatization-what-ba782b7c0bd8 [accessed 10/05/20]

n-grams of the language's words in order to implicitly obtain suffix-stripping rules.[55] In the field of text mining there are three different derivation algorithms: the *Porter stemmer*, the *Lancaster stemmer* and the *WordNet stemmer*. In general, what we expect from a good stemmer is that it recognizes, with the greatest possible precision, the correlation between terms to which we attribute a common semantics, and that it uses this correlation to replace all related terms with the corresponding theme (Porter, 2001).

All of these principles are now applied to the textual dataset composed by 156 interviews, described in Section 3.6. The aim is to create a text corpus and a BoW matrix. For this purpose, some functions belonging to the tm and SnowballC package are used. First of all, VCorpus() function enabled to create a text corpus composed by 156 interviews. Subsequently, tm_map() function pre-processed it. Specifically, it enabled to:

- Uniform the characters by converting the text into lower case in order to prevent the algorithm from considering terms like "alexa" and "Alexa" as having different meaning.
- Remove punctuation and numbers to prevent the algorithm from considering terms like: "alexa", "alexa1" and "#alexa" as different elements.
- Remove the stopwords since they do not have any meaning and they are not relevant for analysis purposes.
- Activate the stemming process in order to reduce the vocabulary size, obtain an efficient collection of words and avoid the problem of useless multiple counting.

```
#creating and cleaning corpus of reviews
library(tm)
library(SnowballC)
corpus = VCorpus(VectorSource(dataset$incident))
#converting to lowercase
corpus = tm_map(corpus, content_transformer(tolower))
#removing punctuation
corpus = tm_map(corpus, removePunctuation)
#removing numbers
corpus = tm_map(corpus, removeNumbers)
#removing stopwords

corpus = tm_map(corpus, removeWords, stopwords("english"))
```

The pre-processing phase led to the development of a *WordCloud*, also known as *text cloud* or *tag cloud*, represented in Fig. 3.3. It is a way to visually represent textual data. Specifically, it displays the most frequent words within the corpus and gives highest relevance to *keywords.* Each word within the cloud has a different size based on the number of times it appears in the interviews: the larger the size, the higher the number of times the keyword appears.

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[55] *Devopedia.com:* https://devopedia.org/stemming [accessed 11/05/20].

Fig. 3.3. WordCloud

The WordCloud obtained provides a representation the most frequent words within the 156 interviews. Looking at Fig. 3.3 we can see that the main terms are "Alexa", "Like", "Home", "Artificial", "Time", "Amazon", "Assistant", "Useful", "Intelligence", "Technology", "Device", "Google" and "Buy". In this way we can get an early idea of the most discussed topics that will be better described with the application of Topic Modeling algorithms in Section 3.8.

Now that the text corpus has been pre-processed, it is possible to extract the frequency of each term. The next step consist into the creation of a matrix, named “tdm”, by using the TermDocumentMatrix() function.

```
tdm = TermDocumentMatrix(corpus)
```

The resulting matrix contains 156 documents (interviews) and 2542 terms with 97% sparsity. Such level of sparsity suggests that within the text of the interviews there are a lot of words that appear few times. However, a high percentage can also be explained by a huge amount of textual data. Therefore, in order to better assess the relevance of the various terms contained in the interviews, the *weighting value* could be adopted as an indicator. This metric measures the frequency of occurrence of each word in each interview and, therefore, ponders its weight within the collection. In the tdm matrix, each column correspond to an interview, each row correspond to one of the terms used in the whole collection and each cell indicates the frequency of the term for each interviews. Now machine learning algorithms can be applied on the BoW matrix built. The Bag Of Words model has found large support and application on prediction model like language modelling and document classification due to its simplicity to be understood and implemented and its flexibility for customization on a specific text dataset. However, it deals with three main issues. First, the vocabulary has to be accurately structured in order to manage the size, which has effects on the sparsity of the document representations. Second, sparse text representation are more challenging to be processed, since the models have to extract few valuable information in a large representational space. Third, and last issue, is related to the meaning of words. Indeed, the BoW model ignores the word order and, thus, their context and their meaning in the text (semantics).[56] Despite these limitations, the BoW is considered as the standard text representation to develop machine learning linear text classifiers, due to its ability to extract enough relevant information and make accurate predictions. In this perspective, the occurrence frequency of each word represents the feature that will be subsequently used to train these text classifiers (Porcu, 2016).

3.8 Topic Modeling Method

In this section it will be illustrated the application of the Topic Modeling method, an unsupervised machine learning technique, that, in other words, does not require any training. In the context of Natural Language Processing (NLP), it is a method aimed at detecting hidden structure in a collection of documents. Therefore, it enables to examine a text, identify terms and phrase pattern and automatically classify groups of words and similar expressions that represent and characterize the set of documents.[57] Specifically, the algorithm makes it possible to discover latent topics within a collection of documents, associate them to the identified topics and finally use the calculated association to organize and interpret the textual data. Topic Modeling is commonly applied for text classification, recommender systems and to uncover themes in texts. Text classification consists in grouping similar words in topics. Recommender systems consists in recommending to the user contents whose topic structure is similar to those one has shown interest in. Uncovering themes in texts enables to identify trends online.[58] In summary, Topic Modeling is one of the most common unsupervised machine learning technique that enables to understand, organize and summarize a huge amount of textual data in order to discover hidden topic patterns, categorize documents according to these topics and organize, search and summarize easily texts (Blei & Jordan, 2003).

Specifically, in this section the Topic Modeling method is applied to a collection of 156 interviews. The objective is to group them on the basis of the main topic discussed. In each interview, multiple topics could be discussed in different proportions: in each of them one will expect to find a quantity of words related to a specific topic in proportion to the weight of the latter in the text. The Topic

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[56] Browniee, J. (2017). *A Gentle Introduction to the Bag-of-Words Model.* In Deep Learning for Natural Language Processing. Available at: https://machinelearningmastery.com/gentle-introduction-bag-words-model/ [accessed 10/05/20].

[57] *Monkeylearn.com:* https://monkeylearn.com/blog/introduction-to-topic-modeling/ [accessed 06/06/20].

[58] *A complete guide to Topic Modeling.* Available at: https://nlpforhackers.io/topic-modeling/ [accessed 19/05/20].

Modeling captures this insight into a mathematical framework that allows to examine a set of documents and find out, based on the statistics of the words in each of the interviews, which topics are covered and their weight within the text document. Among the most popular algorithms used to apply this method, it is worth mention the Latent Dirichlet Allocation (LDA). The basic assumption is that each document is considered as a set of topics, each of which is characterised by a particular distribution of terms and words.[59] It is a generative probabilistic model, used in the study of natural language, which makes it possible to extract topics from a set of documents and to provide a logical explanation of the similarity of individual parts of the documents.[60]

Starting from the BoW matrix, the LDA algorithm considers every interview as a vector of word count. Each interviews is expressed as a probability distribution over some topics, and each topic is expressed as a probability distribution over a number of terms. Specifically, the LDA for each interview in the collection detects a topic from its distribution over topics, samples a word from the collection of all words associated with the selected topic and, lastly, repeats this process for all the words within the interview. The basic assumption underlying the algorithms is that each word in the document can be associated to one of the topic discussed. Therefore, each interview can be thought as a mix of the topics in the corpus (Hong & Davison, 2010). One method used by the LDA to identify the topic and learn the topic representation in each document is the so-called "Collapsed Gibbs Sampling". It consists in going through each document and randomly assign each term in it to one of the N topics, where N is chosen initially. It results in a representation of the documents and the words distribution for each topic. In order to improve this process, the algorithm, for each document, goes through each word *w* and compute *p (topic t | document d)*, that is percentage of words within the document *d* associated to topic *t* and *p (word w | topic t)*, that is the percentage of associations, among all document *d*, to topic *t* that comes from the word *w*. Subsequently, it associates the word *w* to a new topic *t'*, the latter is chosen with probability *p (topic t' | document d) * p (word w | topic t')*. It enables to predict the probability that topic *t'* generates the word *w*. By repeating this last step, it is possible to improve the topic association process. In this way is it possible to obtain the topic mix for each document (interview) (Blei & Jordan, 2003).The Collapsed Gibbs Sampling algorithm, thank to its high level of accuracy and speed, has found large application in machine learning and data mining, specifically in classification, web search and recommendation systems (Qiu et al. 2014). Therefore, having clear that the Topic Modeling method considers each interview as a mix of topics in which each topic is represented by a probability distribution on words, we will see how this technique has been applied to our dataset and we will illustrate what are the results obtained by using the tidytext

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[59] http://www.andreaminini.com/semantica/latent-dirichlet-allocation-lda [accessed 08/05/20].
[60] *Okpedia.it:* https://www.okpedia.it/latent_dirichlet_allocation [accessed 09/05/20].

principles. The functions to perform the algorithms on the interviews requires to install three specific packages, namely tidytext, topicmodels and dplyr. The first step was to create a matrix, named "dtm", using the DocumentTermMatrix() function. In this matrix, each column corresponds to one of the words within the interviews, each raw corresponds to one interviews and each cell indicates the frequency of the occurrence of the specific word in the specific document. Specifically, the matrix contains 156 interviews and 2542 words, with a 97% sparsity. This percentage, as already seen in Section 3.7, indicates a great textual dispersion. Since within the entire collection of interviews many terms appear sporadically, then not all of them will have the same relevance. The greater the frequency of occurrence of a term within the collection of documents, the greater its relevance for Topic Modeling analysis. The next step was to apply the LDA model by using the LDA() function with *k=4* topics, where *k* is an arbitrary value. It is a well-known machine learning technique employed as method of classification to predict categories. For each interview the algorithm selects a topic among the related distribution on the different topics, sampled a word among the distribution of the words associated to the chosen topic and repeated this process for all the terms in the interview.

```
lda = LDA(dtm, k = 4, control = list(seed = 1154))
```

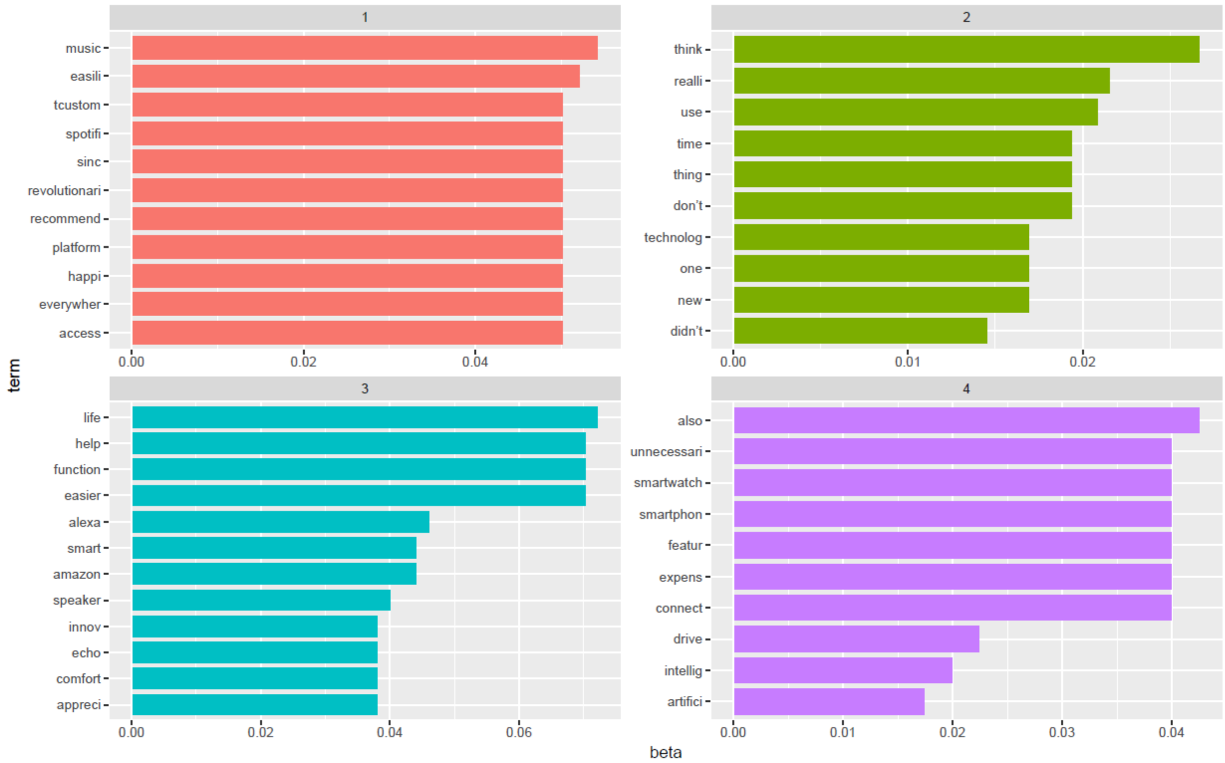
It this way it was possible to obtain an association between words and topics and between topics and interviews. Next step was to convert the lda format in a tidy data frame, named “topics”, which resulted in a probability of belonging *per-topic-per-word β*. The fig. below shows an extract:

```
> topics
# A tibble: 9,808 x 3
  topic term          beta
  <int> <chr>         <dbl>
1     1 —wouldn't     1.19e- 18
2     2 —wouldn't     2.96e- 96
3     3 —wouldn't     2.90e-  4
4     4 —wouldn't     1.41e- 97
5     1 'irrationality' 1.78e-106
6     2 'irrationality' 5.04e-109
7     3 'irrationality' 1.28e-102
8     4 'irrationality' 3.00e-  4
9     1 'watched'     2.15e-  4
10    2 'watched'     8.78e- 95
# … with 9,798 more rows
```

Note that this function has transformed the model into a *one-topic-per-term-per-row* format. For each combination, the model calculates the probability *b* that that term is generated from that given topic. For example, the term “irrationality” has a 1.78e-106 probability to be generated by topic 1 and a 5.04e-109 probability to be generated by topic 2.

Fig. 3.4 below illustrates four topics have been generated using the 10 most common terms within each of them.

Fig. 3.4. 4-topic LDA Model



The graphic representation above enables to distinguish the four different topics extracted from the collection of interviews. The most common words associated to topic 1 are “music”, “recommend”, “platform”, “everywhere” and so on, which suggest that the topic discussed is “Spotify”, a subscription-based digital music service. The most common words associated to topic 2 are “think”, “use”, “time”, “technology”, “new” and so on, which suggest that the topic discussed is “time saving”, which is one of the main advantages that these innovative technologies have in common. The most common words associated to topic 3 are “life”, “help”, “function”, “easier”, “alexa”, “smart”, “amazon”, “speaker” and so on, which suggest that the topic discussed is Alexa, the virtual digital assistant developed by Amazon. The most common words associated to the fourth, and last, topic are “smartwatch”, “connect”, “feature”, “smartphone”, “expens”, “unnecessari” and so on, which suggest that the topic discussed is the “Smartwatch”, a smart mobile device with a touchscreen display designed to be worn on the wrist.

3.9 Sentiment Analysis

As discussed in Section 3.2, sentiment analysis (opinion mining) is a particular type of natural language processing that focuses on the analysis of text in order to automatically detects and extracts sentiments, emotions, opinions about any entity, namely "opinion target", which can be a product, a service, a business, an individual, a topic and much more. It has several applications and brings considerable benefits to businesses in every field. Sentiment analysis focuses on identifying how sentiments are expressed within the text documents, their polarity (positive or negative) and polarity strength, and the relationship between the sentiment and the opinion target. More in detail, it is possible to identify several sub-activities, all related to the tagging of a given document based on the opinion expressed (Pang & Lee, 2004):

- Binary text categorisation into two classes (objective and objective). A text is objective if it has a factual nature and, therefore, describes a particular event, without expressing any positive or negative opinion about it. A text is subjective if it contains an opinion on the topic.
- Determination of the sentiment polarity (positive or negative) of the document depending on the opinion expressed in it about the topic.
- Determination of the sentiment polarity strength, which is the intensity level of the opinion. For example, a negative opinion can be classified as slightly negative, negative or strongly negative.

Specifically, in this study, the sentiment analysis is performed on a dataset composed by 156 interviews in order to detect the general polarity and polarity strength toward any smart product and smart service. The first step, discussed in Section 3.9.1, was to extract, using the tools offered by the tidytext package, the *sentword* within the overall corpus text in order to have a first indicative measure of the polarity of the collection. In Section 3.9.2, the goal was to identify, quantify and classify the sentiment contained in text. The comparison between the results obtained with three different lexicons gave us a broader perspective to better understand the sentiment orientation of the interviews. This analysis enabled to obtain interesting insights on respondent's impressions towards any artificial intelligence embedded product or service.

3.9.1 *Sentiment Words*

By using the tidytext and dplyr packages, it was possible to obtain a complete list of *sentiment words* contained in the interviews with their related frequencies. It enabled us to have an overall idea of the polarity of the collection. First, the list of words from the rows of the comments vector "incindet" (i.e. from the interviews) have to be filtered in order to obtain a matrix in which each row corresponds to a word. We have already created this contingency table by converting the corpus into a *term-document matrix* in Section 3.7. Since the tdm matrix objects cannot be used directly with the tidytext package tools, it is needed to convert the tdm matrix into a tidy class data frame, i.e. *one-token-per-document-per-row*, using the tidy() conversion function. *Tokenization* is the process of dividing the text into pieces, called *tokens,* while discarding certain characters, such as punctuation. The *token* is a piece of text or a sequence of characters grouped together and used as a semantic unit for analysis purposes. The token could be a single word, a *n-gram*, a sentence or even a paragraph.[61] The data frame obtained was named "tidy". This object returned a *tibble*, a data frame class that does not convert strings into factors and does not use line names. The size of the tibble is 11529x3 variables where, as shown in the extract below, each of the 11529 rows corresponds to a specific term while the 3 variables are the term, the interview the term belongs to and the occurrence count.

After the conversion, the next step was to identify the sentiment words and categorize them as positive or negative using the bing lexicon as input in the inner_join() function. The bing lexicon, as we will see in more details in Section 3.9.2, consists of 6788 terms and categorizes the words in positive and negative according to a binary classification: -1 if negative, +1 if positive.

```
sentwords = tidy%>%

inner_join(get_sentiments("bing"), by = c(term = "word"))
```

The data frame sentwords is a tibble class matrix with size 909x4, where 909 is the number of lines or the number of sentiment terms that appear in the interviews and 4 is the number of variables: the term, the occurrence count, the interview the given term belongs to and the sentiment (positive or negative). In particular, of the 909 sentiment words that appear in the entire body of reviews, 626 were labeled as positive and 283 were labelled as negative. This enabled to obtain an indicative measure of the polarity of the collection and, thus, gave an idea of the orientation of the interviews.

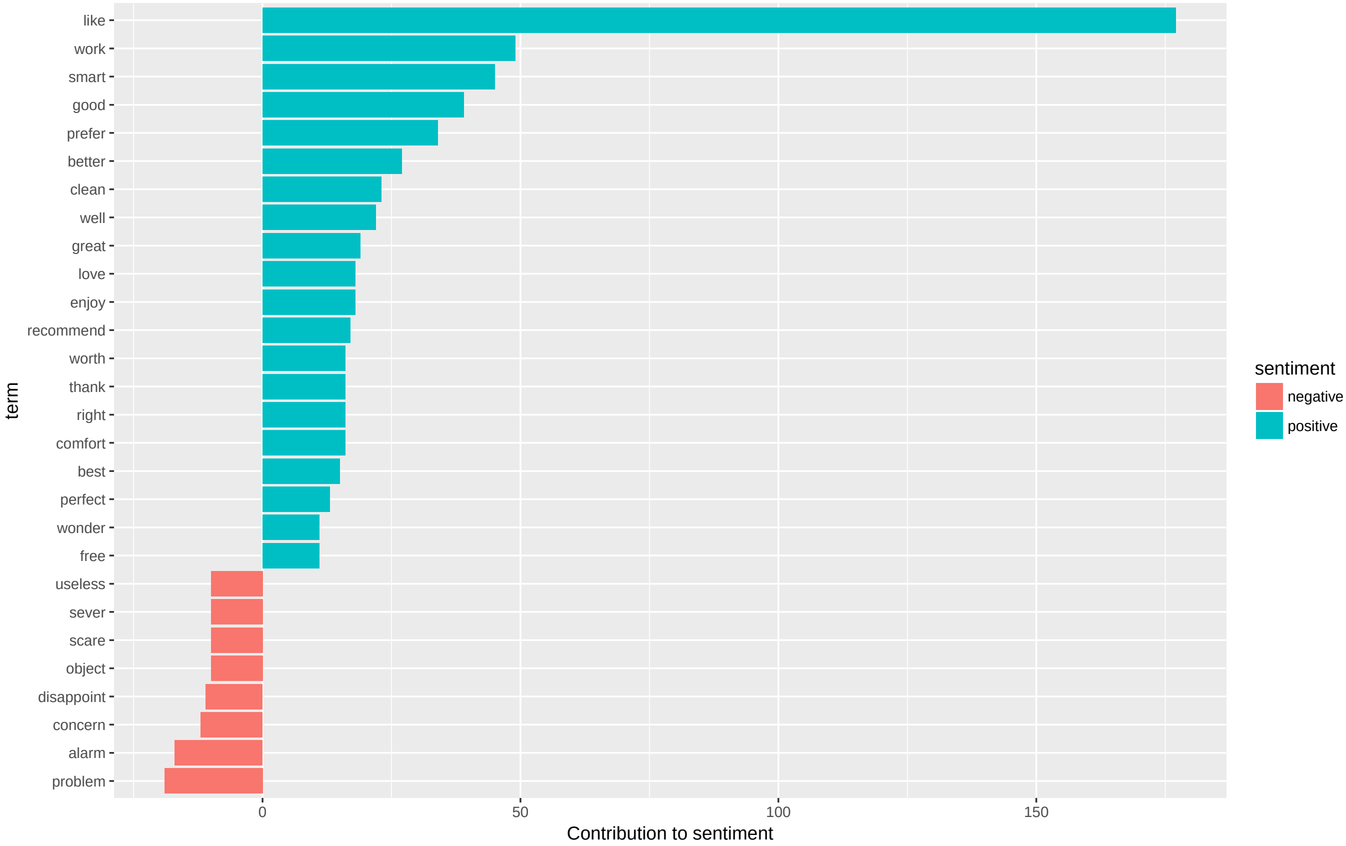
[61] Manning, C. D., Raghavan, P., Schütze, H. (2008). *Introduction to Information Retrieval.* Cambridge University Press. Available at: https://nlp.stanford.edu/IR-book/html/htmledition/tokenization-1.html [accessed 11/05/20].

```
> sentwords

# A tibble: 909 x 4

  term      document count sentiment

  <chr>    <chr>    <dbl> <chr>

 1 difficult 1          1 negative

 2 like      1          1 positive

 3 love      1          1 positive

 4 passion   1          1 positive

 5 prefer    1          1 positive

 6 wonder    1          2 positive

 7 enjoy     2          1 positive

 8 good      2          1 positive

 9 like      2          4 positive

10 work      2          3 positive

# … with 899 more rows
```

Fig. 3.5 provides a clear representation of the sentiment words used in the interviews, specifically, it enables to quickly identify which word contributed the most to positive or negative sentiment. This impact is measured simply by considering the frequency of occurrence of the term (value placed on the ordinate axis in Fig. 3.5): the more it is used within the collection of the 156 interviews, the greater its contribution to the general sentiment.

The most common positive sentiment words shown in Fig. 3.5 are “like”, “work”, “smart”, “good” and “prefer”, while the most used negative sentiment words are “useless”, “scare”, “disappoint”, “concern” and “problem”. We can observe that the positive sentiment words are greater in number and appear more frequently that the negative sentiment ones, thus suggesting that overall polarity of the collection of interviews. In the next section, we will see how to each of these sentiment words it is possible to assign a score in order to determine the polarity of each interviews and, consequently, of the whole body of interviews.

Fig. 3.5. List of terms with that contribute the most to the sentiment



3.9.2 *Sentiment Polarity*

After having classified the sentiment words as positive or negative and identified their relative frequency, the focus of this section is on measuring the intensity of sentiment polarity. A score will be assigned to each interview. To perform this analysis specific functions of the syuzhet package were applied. It enabled to extracts the sentiment from the text by using different sentiment lexicon dictionaries based on unigrams, and, therefore, on single words (Özdemir & Bergler, 2015). The four standards lexicons are: "syuzhet","afinn", "bing", and "nrc" (Naldi, 2019). They can be retrieved by using a specific function which results in a data frame with two columns, one reports the words and the other one indicates their sentiment score. The "syuzher" lexicon, developed by Matthew L. Jockers, is the default one. It includes 10748 words, of which 7161 are negative and 3587 are positive. It assigns a value of -1 to negative words and +1 to positive words. The "afinn" lexicon, developed by Finn Arup Nielsen, has the peculiarity to contain Internet slang and obscene words. It is made of 2477 words, of which 1598 are negative, 878 are positive and 1 is neutral. It assigns a score or -5 to negative words and a score of +5 to positive words. The "bing" lexicon, developed by Minqing Hu and Bing Liu, is composed of 6789 words. Specifically, it has 2006 positive words and 4783 negative words. It assigns a score of -1 to negative words and a score of +1 to positive words. The information about these three lexicons are represented in the Fig. 3.6 below.

Fig. 3.6. Lexicons in the syuzhet package

Lexicon	No. of words	No. of positive words	No. of negative words	Resolution
Syuzhet	10748	3587	7161	16
Afinn	2477	878	1598	11
Bing	6789	2006	4783	2

Source: Naldi, 2019

If we compare the size and the resolution, i.e. the capability to assign different scores of sentiment by using multiple value, of the three lexicon, we can notice that the "afinn" lexicon is the smallest, the "bing" lexicon has the lowest resolution, while "syuzhet" is the best one in terms of both size and resolution.

The fourth, and last, lexicon is different from those considered so far. It contains 13889 words that are distributed among eight emotional categories shown in Fig. 3.7 below.

Fig. 3.7. Words in the nrc lexicon

Category	No. of words
Anger	1247
Anticipation	839
Disgust	1058
Fear	1476
Joy	689
Sadness	1191
Surprise	534
Trust	1231
Positive	2312
Negative	3324

Source: Naldi, 2019

It is worth emphasizing some of the drawbacks of these approaches. They score each word in isolation and ignore modifiers. It means that intensifiers like "very" or "extremely" and negations have no effect. Consequently, the sentence "I am not excited today", "I am very excited today" and "I am excited" have the same positive valence. For the same reason, the algorithms do not take in consideration the multiple meanings of words. Indeed, neutral words such as "well" and "like" are often marked erroneously as positive. Furthermore, they only counts a word once for each sentence and do not consider if it is repeated. Lexicon like "bing", that assign every word a value of -1,0 or +1, does not enable to highlight clear differences between words which, although they have the same polarity, may have different intensities. Furthermore, these lexicons do not automatically identify sarcasms and irony. A last observation concerns the size of the text fragment on which we sum the scores assigned to the unigrams and its possible effect on the analysis. Unlike short texts, which are reduced to a sentence or paragraph, long texts can have as a result an average score around 0. Therefore, considering all the limitations of this type of analysis, the overload of sentiment terms can lead to a misclassification (Swafford, 2015).

The analysis of the sentiment polarity of the interviews requires to consider the whole text as a combination of words and its sentiment content of 156 interviews as the sum of the sentiment content of each term. From a computational point of view, by inserting one of the three available lexicons in the syuzhet package as input to the get_sentiment() function, to each term in the comments vector of the interviews, is given a score according to the criteria of the specific lexicon chosen.

```
afinn = get_sentiment(dataset$incident,method="afinn")
bing = get_sentiment(dataset$incident,method="bing")
nrc = get_nrc_sentiment(dataset$incident)
```

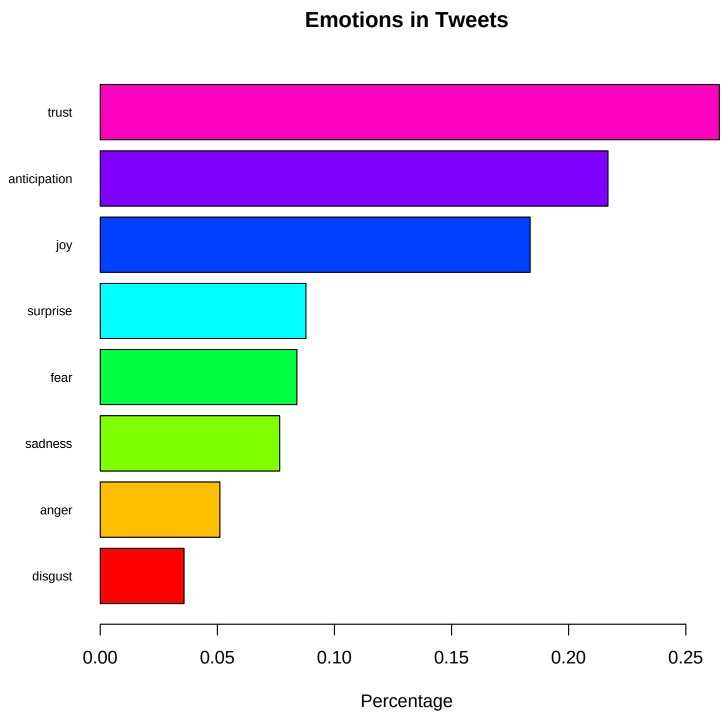
Subsequently, by algebraically summing up the scores assigned to the words of each single interview, a total sentiment value, which measures the polarity intensity, is obtained for each of them. Fig. 3.8 illustrates for each lexicon, the applied syuzhet package function, the corresponding total score and other descriptive statistics such as the average, median, minimum value, maximum value and standard deviation. With the application of the "nrc" lexicon we did not obtain any score, since it only classify sentiment words in eight sentiment categories previously mentioned without assigning any value.

Fig. 3.8. Description of Lexicons and Polarity Results

lessico	funzione	punteggio	min	mediana	media	max	sd
Afinn	get_sentiment itera sul vettore incident e restituisce i valori di sentiment in base al metodo "afinn"	1495	-5	7,5	9,583	52	9,5
Bing	get_sentiment itera sul vettore incident e restituisce i valori del sentiment in base al metodo "bing"	633	-5	3	4,06	22	4,3
Nrc	get_nrc_sentiment calcola la presenza di otto differenti emozioni e la rispettiva valenza all'interno del vettore incident	-	-	-	-	-	-

The *barplot* in Fig. 3.9 shows the distribution of the eight emotions provided by the nrc lexicon within the corpus of interviews. In particular, the abscissae axis indicates the percentage of the interviews characterized by the specific emotional class listed on the ordinate axis.

Fig. 3.9. Sentiment Distribution Barplot



We can observe that positive sentiments such as trust, anticipation and joy far outweigh negative sentiments. This is also a measure of the polarity of the interviews, expressed differently from the output provided by the afinn and bing methods, but it is equally informative. Although the three different lexicons provide different absolute results, they show similar polarity trends.

3.10 Content Analysis

Content analysis (CA) is a research methodology dealing with the content and the meaning of a text, often unstructured (Gheyle & Jacobs, 2017). This tool is used to identify the presence, meaning and relationships of specific words and concepts within a text. It applies an inductive or deductive process in order to make inferences from certain premises and samples and move from unstructured text to answer a specific research question (White & Marsh, 2006). Therefore, it can be formally defined as "*a research technique for making replicable and valid inferences from texts (or other meaningful matter) to the contexts of their use*" (Krippendorff, 2004). The broad category of "text" includes books, essays, newspapers, speeches, advertising, informal conversation, interviews and any other occurrence of communicative language. Given its multiplicity of applications, it is currently used in a variety of fields, such as marketing, media studies, gender and age issues, sociology and political science, psychology and much more. Berelson (1952) listed some of the possible use of content analysis: identify international differences in communication, identify the existence of propaganda, detect the intentions, focus or communication trend of an individual or a group, identify attitudinal and behavioural responses to communication and, lastly, determinate the emotional or psychological state of individuals. Content analysis requires to code (or break down) the text into multiple manageable different variety of level categories (word, word sense, phrase, sentence or theme). The categories identified are the object of analysis that can be conducted by applying one of the following two basic methods[62]:

1. *Conceptual analysis:* it enables to study the existence and frequency of specific concepts expressed by words of phrases in a given text. First, it is required to state a research question and identify a sample. Subsequently, the text must undergo to a coding process, which is a selective reduction, that consists in organizing it into manageable content categories consisting of a word, a set of words or phrases relevant to answer the research question. With this kind of analysis, the researcher only wants to investigate the presence of specific words and quantify them, ignoring any possible relationship between them.
2. *Relational analysis:* also known as semantic analysis, it enables to investigate the existence of semantic or meaningful relationships among the concepts in the text identified with the above mentioned analysis. It is based on the assumption that each individual concept has no inherent meaning. The latter results from their relationship within the text.

Furthermore, this methodology can be flexibly applied in a quantitative or qualitative setting (White & Marsh, 2006). The quantitative approach is a deductive method consisting in the generation of hypotheses, the sampling of data and a clear a priori definition of categories and unambiguous coding rules. After the coding step, the results are analysed through statistical tools (Gheyle & Jacobs, 2017). Even the qualitative approach of content analysis requires the formulation of a research question, the definition of a sample and the identification of categories and coding rules (Kaid & Wadsworth, 1989). Hsieh and Shannon (2005) formally define it as "*a research method for the subjective interpretation of the content of text data through the systematic classification process of coding and identifying themes or patterns*". It is an inductive process and differs from the quantitative approach with respect to categorization and coding: categories and coding schemes are not a priori defined. Categories are constructed while reading through the text and the resulting evidence is as important as the initial questions guiding the entire research (White & Marsh, 2006). It has the advantages of

[62] *Introduction to content analysis*. Available at: http://www.umsl.edu/~wilmarthp/mrpc-web-resources/content-analysis.pdf [accessed 12/05/20].

preserving the benefits of the quantitative approach while giving more attention to the implicit theory behind the categories (Mayring, 2000). Indeed, it goes beyond the mere count of words and focuses on the meaning behind the text and the existence of semantic relationships (Weber, 1990). As well as the quantitative content analysis, it also requires to conduct descriptive statistics and verify the trustworthiness. Despite the differences above described between the two approaches, many scholars doubt the existence of an effective dichotomy between quantitative and qualitative content analysis: any text can be first approached qualitatively and then converted into numbers (Krippendorff, 2004). Morgan (1993) has instead defined content analysis as a quantitative analysis of qualitative data. In conclusion, we can think of content analysis as a set of methods positioned on a continuum that goes from a very quantitative to a very qualitative approach.

This study approaches content analysis in a qualitative way. The analysis will be conducted on 156 interviews organized in the dataset presented in Section 3.6. Specifically, the total collection contains 70 positive interviews in which respondents were asked to think and describe a recent episode of AI innovation adoption and how they felt, and 86 negative interviews in which respondents were asked to think and describe a recent episode of AI innovation resistance and their emotions. The aim of this analysis is to investigate and identify inductively the most discussed reasons to resist and to adopt any kind of AI innovation. The interesting results emerged are illustrated in the subsequent sections.

3.10.1 *Reasons for IoT Innovation Resistance*

Desire to Maintain Control over Habits

Literature defines habits as one of the main causes of customer resistance, since a typical human tendency is to strive for consistency and status quo (Sheth, 1981). Artificial Intelligence (AI) tools, with their multiple functions and features, do ordinary and effortless tasks that individuals are always being used to accomplish on their own. Therefore, the adoption requires changes in established routines and behaviours. This is associated to the concept of *pervasiveness*, which refers to the extent to which an innovation requires behavioural changes or adjustments (Barnett, 1953). From the analysis emerged that individuals enjoy and feel comfortable in performing these activities, like searching for information, and, therefore, they tend to resist the possibility that a device could replace them. However, resistance to change is not the only reason that prevent adoption. Despite they recognize the convenience and the advantages in the usage of such devices in certain circumstances, they have expressed concerns about a possible loss of control over their life and time and a fear that technology could "carry them away". Therefore, individuals resist adoption to prevent that any aspect of life could be regulated and managed by it. This barrier resulted to be particularly relevant for usage decisions of systems like Alexa and Siri, two virtual assistants developed respectively by Amazon and Apple.

Lack of Perceived Usefulness

Perceived usefulness is the degree to which a person believes that the use of a particular system could enhance the job performance. When a technological innovation is high in perceived usefulness, the individual will believe in the existence of a positive relationship between the use and the performance results (David, 1986). In the context of IoT innovation, it is associated to the concept of relative advantage, defined as the extent to which the innovation is better than what it substitutes. Specifically, Rogers (1995) suggested that an innovation will be more easily adopted when it provides clear and unambiguous advantages. With regard to smart products, perceived usefulness refers to the benefits the customer thinks will receive from the use of the device, such as saving time, convenience, access to additional information and new uses. From the content analysis conducted in this study, the absence of these characteristics emerged as a cause of customer resistance. Smart devices' functionalities can easily be performed by individuals without any technological support and with little effort. Therefore, individuals expressed a lack of the perceived need to adopt such AI innovation. These reasons resulted to negatively impact customer decision to use smart systems such as the smartwatch, Amazon Echo, an intelligent speaker that can be controlled by voice thanks to Alexa's assistance, and Siri. In summary, these devices are perceived as useless and as not having any additional advantage especially if the user has a smartphone or a computer.

Perceived Price

Perceived price is defined as the individual perception about the price of the product (Zeithmal, 1988) and, in the context of innovation resistance, it refers to the perceived value. Customers perceive the price as a monetary sacrifice (Kim et al., 2007) and what is given up to obtain the innovation (Zeithmal, 1988). Specifically, if the innovation does not offer a better performance-to-price ratio than the product substitutes, it would encounter a high resistance. Studies evidence that a low performance-to-price ratio is the most significant obstacle for consumers to adopt innovations (Parasuraman & Grewal 2000). It can be associated to the concept of relative advantage. From this study emerged that the perceived price is one of the main reasons of resistance to smart products. Specifically, the price is considered a barrier for three main reasons. First, these devices are mainly perceived as useless with low economic benefits, therefore for individuals they are not worth their high price. This barrier arises especially for devices like the smartwatch and the smart speaker, since they are perceived as mere "gadget" and futile objects. Second, to work effectively and exploit all the functionalities, it is required that multiple devices are connected to each other and the installation, repair and maintenance of the entire system is very expensive. Third, devices like Amazon Echo and the HomePod, applications like Waze, systems like Siri are perceived as being not sufficiently developed. The algorithms, the machine learning process, the sound and many other features should be improved. Therefore, they appeared as not meeting user's expectations in terms of quality. One of the main factors that disappointed respondents the most is the perception that the intelligence of devices like Alexa, for instance, cannot be compared to that of human being as the apathy and the limited computing capacity is tangible. Furthermore, respondents found frustrating that voice assistant, like Siri, do not properly understand the user's requests. Another feature that should be improved is the battery life. Therefore, individuals resist adoption and prefer to wait for advanced and improved versions.

Functional Risk

Risks arise due to the uncertainty and potential negative consequences associated to the adoption of an innovation that cannot be anticipated (Ram & Sheth, 1989). When customers are aware of the risk, they tend to delay the adoption in order to search for additional information and learn more about the new product. In this study, the functional risk resulted to be particularly relevant in shaping customer adoption decision. It is related to the performance uncertainty that arises from the concern that the device could not function properly. It emerges in regard to home appliances, like the refrigerator or the washing machine with AI integrated. They can be activated even if the owner is not at home and it could be dangerous in case of malfunctions, because one cannot act promptly to contain the damages.

Preference for Human Interaction

Tradition barriers, a particular type of psychological barrier, arise when customers perceive that the innovation threats their culture and tradition and it is incompatible with their existing value, past experiences and social norms. The greater the deviation from established traditions required by the adoption of an innovation, the greater the resistance it will encounter. It can be associated to the customer need to have a certain degree of human interaction (Laukkanen & Kiviniemi, 2010) and to avoid machines (Dabholkar & Bagozzi, 2002) during the service experience, since it represents a social opportunity both for customers and sales personnel (Dabholkar, 1996). In this study, this need resulted to be particularly impactful for adoption decisions towards IoT innovation. In the service context, respondents reported a preference for the traditional store since the use of artificial intelligence would only provide benefits in an online shopping context, in which, for instance, clothes and make up cannot be tried on. Furthermore, the questions one ask to devices like Alexa could have been the source of spontaneous conversations between members of the same family. Therefore, individuals are concerned that, in the future, these conversations will no longer take place among people and will be replaced by simple commands imposed by humans to electronic devices. For this reason, individuals prefer to preserve the traditional human interaction alive as long as possible rejecting the usage and adoption of these technologies.

Privacy Concerns

Privacy can be defined as "*the right to select what personal information about me is known to what people"* (Westin, 1968). With the proliferations of IoT products and services characterized by a continuous exchange of information and data, privacy has become a critical issue. These technologies are characterised by pervasiveness, invisibility, ubiquity and invasiveness (Slettemeas, 2009). They collect and manage a huge amount of data and personal information (Sicari et al., 2015). Evidence from this analysis shows the privacy's critical role in shaping user's intention to adopt. Specifically, the loss of control over personal or private information, the possible improper access and unauthorized secondary use resulted to be the main cause of privacy concerns. It is well-known that smart devices like Google Home and Alexa to work efficiently require a constant collection and exchange of data, most of which are private and personal information about the owner. They have the microphone always turned on and could potentially listen and record whatever happens at home. This increases users' perception of being *"subtly listened",* controlled and observed. Therefore, individuals perceive that such devices are intrusive and violate their privacy. *Intrusiveness* refers to technology's capability to enter in customers' life without their permission (Mani & Chouk, 2017) and it has a negative impact on individual behaviour, since it leads to negative emotional reactions, like the feeling of irritation in the case of advertising (Edwards et al., 2020). Customers need to perceive they have a certain degree of control on their personal data and the idea of sharing them with unknown sources makes them feel uncomfortable. It was interesting to note that also simple questions coming from Siri, for instance, like *"would you like to continue listening to music?"* are perceived as too invasive. These concerns create a huge psychological barrier that leads to innovation resistance.

Network Externalities

Network externalities can be defined as "*the value or effect that users obtain from a product or service that will bring about more value to consumers with the increase of users, complementary products or service"* (Katz & Shapiro, 1985). Therefore, the value of any smart device increases as the number of users or complementary products increases. It is associated to the concept of perceived complementarity, defined as "*the availability of function or applications serving to fill out or to complete IoT services"* (Hsu & Lin, 2016, p. 519). From this study emerged that perceived complementary has a significant impact on perceived benefits that, in turn, contribute to predict attitudes towards the adoption and usage of IoT innovations. This resulted to be particularly relevant for smart speakers. Indeed, in order to completely exploit, take full advantage and enjoy all their functionalities and potentials, they need to be part of a “smart home”. However, creating such smart ecosystem is both complex, expensive and time-consuming since it would imply radical changes in the house furniture. For this reasons most of respondents reported to have postponed or rejected the adoption.

Complexity/Ease of use/Self-efficacy

Perceived complexity deals with the difficulties of using and understanding the new technology (Kleijnen et al., 2009). The higher the complexity of an innovation, the higher the relative customer resistance (Ram, 1987). It is related to the concept of perceived ease of use, which is the degree to which a person believes that using a particular system would be free of effort. When a technological innovation is perceived as easy to use, it has a higher likelihood to be adopted (David, 1986). From the analysis of the interviews, the perception of innovation complexity resulted to be a significant barrier to adoption. Specifically, with regard to AI-built innovation, it arises mainly because creating a smart environment at home requires to substitute all the old not connected objects with the new ones. A number of respondents reported to have difficulty in understanding how these devices work and in installing and connecting them. Furthermore, they have to download many apps and connect them to Alexa, for instance. All of these practices are perceived as complex, time-consuming and challenging. The amount of cognitive effort required is perceived as higher than the expected benefits. This can also be associated to the concept of *self-efficacy*, defined as the individual’s perception of his or her ability to use technological innovations (Compeau & Higgins, 1995). Findings demonstrates that it is critical for customers to perceive that they are able to understand how these devices work. All of these factors emerged as significant reasons cons the adoption and use of smart systems.

Vulnerability (Anxiety and Dependence)

Vulnerability can be defined as a state of helplessness, loss of control and dependence (Baker et al., 2005). This state is enhanced as the importance of technology grows in our society (Shu et al., 2011). It is related to the concept of technological dependence and technology anxiety. Technological dependence is defined “*as a psychological state that provides a sense of being overly dependent on, and a feeling of being enslaved by, technology*” (Ratchford & Barnhar, 2012, p. 1212) for accomplishing tasks or reaching specific goals. It is also influenced by the perception that the use of technology reduces autonomy. Technology anxiety is associated to the feeling of fear and apprehension for the use of new technology (Igbaria & Parasuraman, 1989). This study evidenced the relevance of these psychological states in shaping customer adoption decision in the IoT context. Specifically, they mainly derive from the perceived possible negative effects of machines on people. The most mentioned concerns are related to the feeling of isolation and addiction that is originated from the use and abuse. Technology makes people feel connected but more “physically distant” and alone. Respondents reported that technology is also perceived as a source of stress that threat their freedom and makes them feel oppressed. They are concerned of loosing their “human” nature and the contact with reality. Most of them feel uncomfortable when interacting with machines due to the fear of being manipulated. These perceptions give rise to significant psychological barriers that discourage customer adoption.

Skepticism

Skepticism refers to individual tendency to doubt, question and disbelieve (Bunge, 1991). The analysis evidenced the role of skepticism as a significant psychological barrier that cause customer resistance towards the IoT devices and the related promised benefits. What respondents questioned the most is devices actual usefulness and performance effectiveness. They prefer to rely on their personal abilities and efforts due to a lack of trust in the innovation outcome.

Negative Perceived Image

Image barriers arise in relation to an unfavourable innovation image the customer perceives due to association between the innovation identity and its origins (product class, industry or country of manufacture). Four negative images emerged from the analysis. First, smart devices are perceived as mere “gadget” and futile objects. Second, they are considered “trends” destined to become obsolete soon. Third, they lack perceived added value. Fourth, they are associated to the concept of laziness; we are all getting facilitated by electronic devices in our daily life and it is perceived as creating a huge damage. This barrier can trigger off resistance in particular towards two IoT devices: smartwatch and smart speaker.

3.10.2 *Reasons for IoT Innovation Adoption*

Time Saving

Among the multiple advantages of AI innovation reported by respondents in the interviews, time saving is one of the most discussed. Movie streaming services, like Netflix and Amazon Prime Video, suggest users’ alternatives on the basis of their personal tastes thus reducing the time required to search among a vast library of films. Roomba, an autonomous robotic vacuum cleaner, is considered as having brought an efficient help to daily life of all those people who cannot spend a lot of time cleaning the house. Service chat with artificial intelligence helps users find solutions to their problems, make orders and obtain quick answers by simply interacting with it and this enables them to save the time required to call a call center or to go to the physical shop. Amazon provides suggestions on what could be interesting for the user thus reducing the time needed to search on the website. In summary, all of these advanced technologies represent a concrete help for those who, for any reason, have no time to perform these activities enabling a significant time saving.

Recommendation System

Movie streaming services, such as Netflix, Infinity and Amazon Prime, use artificial intelligence to "learn with experience". It means that, on the basis of the user's watching history and thus on what one has previously watched on the platform, the movie library is customized, giving advices on movies and TV series that could be interesting for the user. Spotify, a music streaming service, has the same feature. It suggests "weekly discoveries" or "daily mixes" that are personalized playlists based on the music previously listened on the platform. In these playlists there are songs that the user has not heard before but that are likely to be enjoyed. Therefore, artificial intelligence help users discover new contents that best fit their profiles. This feature is considered by respondents a significant advantage and a source of satisfaction, loyalty and increased time usage.

Make Life Easier

One of the most discussed advantage of AI innovation is their ability to make user's life easier by simplifying all the daily activities *"since the moment you get up to when you go to sleep".* This feature is making AI an essential component in life. Applications like Google Maps and Waze help find the way to get somewhere in case of getting lost and provide clear and accurate information about the time require to reach a specific place. They detect traffic and car incidents and suggest the user alternative routes. Devices like virtual keyboard enable users avoid the need to bring heavy books with them. Smart devices can learn the user's habits and can get them up at the same hour, tell them which a good time is to go to the bed, control the sleeping routines and provide reminders for appointments. Roomba simplify everyday *"boring tasks"* such as cleaning the house even when the owner is not present. Smart speakers, such as Alexa or Google Home, with their multiple functionalities, significantly help the user by providing information quickly and by performing different activities. Therefore, from the analysis conducted emerged that a significant incentive to adopt and use technology is its ability to make life easier and more efficient.

Unconstrained Access and Use

Movie and music streaming services and applications have the big advantage that can be accessed everywhere in every moment of the day enabling users to enjoy their contents without constrains.

Smart home devices can be activated even if the owner is not at home and can perform actions having effects in one room even if the user is in another room. The only requirement is the Internet connection. From the analysis emerged that these features positively impact on customer’s decisions to adopt such AI innovations.

Perceived Usefulness

Perceived usefulness is the degree to which a person believes that the use of a particular system could enhance the job performance. When a technological innovation is high in perceived usefulness, the individual will believe in the existence of a positive relationship between the use and the performance results (David, 1986). In this study emerged that perceived usefulness is a significant reason pro the adoption of smart devices. The smartwatch, by connecting with the smartphone, with its multiple features, enables the user to see messages, check for notifications, search information online, answer a call, user SIRI, without the need to use the phone. It also measures the sport activities, how many km one has walked and the heartrate. The latter resulted to be particularly useful for people that have the necessity to do it multiple times a day for clinical reasons. Another mentioned useful AI system is the Bluethooth Voice Recognition for car which enables the user to connect the smartphone to the car and access music, phone numbers, make calls while driving just by stating voice commands. Uber is also considered a particularly useful, cheap, safe and efficient service. It records the most frequent routes, preferences, recurring times and when the user access the app it suggests the hypnotized final destination by using intelligent algorithms. Intelligent chats are also considered useful by individuals that need to ask questions to service providers and receive quick answers. Smart speakers are considered extremely efficient and helpful in providing adequate answers and in performing the required activities. Recorder and translator app understand and remember every word someone says requiring a minimum cognitive effort of the user. Therefore, due to their high perceived usefulness, most of respondents expressed their positive attitude and positive intention in the usage and adoption of such AI innovation.

Human Traits

A particular feature that significantly influences customer decision in using and adopting AI integrated products and services is their “human trait”. Users feel attracted and fascinated in interacting with an intelligent machine that is programmed to think, speak and act as a human. They treat these devices as a real person, they enjoy seeing how a robot handles different situations and requests and remain surprised for their efficient performances. *“I was impressed for how Alexa was programmed to do literally anything you ask her to.”* Furthermore, some respondents reported that, due to their human characteristics, interacting with such machines makes them feel comfortable and not alone. They are also considered a source of entertainment even in social situations with other people, like family members or friends.

Conclusion

This thesis adopted a quantitative and qualitative approach to textual analysis and examined all the results with respect to the research question in order to provide a greater clarity on the nature of the factors of innovation adoption and innovation resistance in the specific IoT context and to identify, quantify and classify customers' emotions towards such innovation.

For this purpose, after having introduced the Internet of Things (IoT) phenomenon and having provided the theoretical tools to comprehend the concepts of customer innovation adoption and customer innovation resistance by reviewing the most relevant academic contributions in this fields, two methods of analysis were applied, namely *sentiment analysis* and *content analysis*.

The analysis was conducted on 156 interviews collected by using the Critical Incident Technique (CIT). Specifically, the total collection contains 70 positive interviews in which respondents were asked to think and describe a recent episode of AI innovation adoption and how they felt, and 86 negative interviews in which respondents were asked to think and describe a recent episode of AI innovation resistance and their emotions.

Initially the Bag of Words approach was applied, and each interview was transformed into a vector that could be used as input (or output) data for machine learning algorithms. Subsequently, the Topic Modeling, an unsupervised machine learning technique, enabled to identify distributions inherent in the set of available data by identifying four topics discussed within the collection. Specifically, among the four topics extracted from the text corpus, three of them refer to specific smart products and services ("Alexa", "Smartwatch" and "Spotify") whereas one refers to one of the most discussed advantage associated to the usage of such technologies ("Time saving").

The sentiment analysis, performed on the total collection of interviews, enabled to detect the general polarity and polarity strength toward any smart product and smart service. The first step was to extract, using the tools offered by the tidytext package, the *sentword* within the overall corpus text in order to have a first indicative measure of the polarity of the collection. By using the tidytext and dplyr packages, it was possible to obtain a complete list of *sentiment words* contained in the interviews with their related frequencies. Specifically, we obtained a representation of the sentiment words used in the interviews in order to identify which word contributed the most to positive or negative sentiment. We could observe that the positive sentiment words are greater in number and appear more frequently that the negative sentiment ones, thus suggesting a positive polarity of the interviews. Subsequently, the goal was to identify, quantify and classify the sentiment contained in text by assigning a score to each interview. The comparison between the results obtained by using three different lexicons gave us a broader perspective to better understand the sentiment orientation of the interviews. Although the three different lexicons provided different absolute results with respect to polarity strength, they showed similar polarity trends: an absolutely positive overall sentiment. This analysis enabled to obtain interesting insights on respondent’s impressions towards any artificial intelligence embedded product or service. Specifically, this could mean that the expectations consumers had were not disappointed after the purchase, resulting in a high level of satisfaction.

The content analysis, a research methodology dealing with the content and the meaning of a text, often unstructured, enabled to investigate and identify inductively, from the total collection of interviews, the most discussed reasons to resist and to adopt any kind of AI innovation. Specifically, the reasons for IoT innovation resistance emerged are: desire to maintain control over habits, lack of perceived usefulness, high perceived price, perceived functional risk, preference for human interaction, privacy concerns, network externalities, high perceived complexity, vulnerability (anxiety and dependence), skepticism and negative perceived image. For what concern the reasons for IoT innovation adoption, the most discussed are: time saving, the recommendation system, the advantage of making life easier, the possibility of an unconstrained use and access, high perceived usefulness and the human traits of such technologies.

These findings could particularly benefit companies. The diffusion and success of most of smart products and services do not have to be taken for granted. Indeed, one of the biggest issue in the Internet of Things (IoT) industry is the low pace of customer adoption of new technologies. Therefore, understanding which are the factors that cause both customers’ resistance and adoption in the specific IoT context is critical to develop and market successfully new products and services. These insights could help firms reduce innovation failure and increase the adoption rate.

Future research could focus on the investigation of innovation adoption and innovation resistance factors by taking into account demographic variables (age, gender and income) of respondents. In addition, a more in-depth analysis could be conducted on specific smart products or smart services in order to identify for each of these the perceived strengths and weaknesses.

R Commands

```
dataset=read.csv("citdata.csv",sep=";",stringsAsFactors=F)


#creating and cleaning corpus of reviews
library(tm)
library(SnowballC)
corpus = VCorpus(VectorSource(dataset$incident))
#converting to lowercase
corpus = tm_map(corpus, content_transformer(tolower))
#removing punctuation
corpus = tm_map(corpus, removePunctuation)
#removing numbers
corpus = tm_map(corpus, removeNumbers)
#removing stopwords
corpus = tm_map(corpus, removeWords, stopwords("english"))
#wordcloud
library(wordcloud)
wordcloud(corpus,max.words=300,random.color=T,min.freq=30,colors=rainbow(50))
#stemming
corpus = tm_map(corpus, stemDocument)
tdm = TermDocumentMatrix(corpus)


#Topic Modeling Method
library(tidytext)
library(topicmodels)
library(ggplot2)
library(dplyr)
library(bindrcpp)
#dtm matrix
dtm = DocumentTermMatrix(corpus)
#cleaning
rowTotals = apply(dtm , 1, sum)
dtm = dtm[rowTotals> 0,]
#lda approach in 4 topics
lda = LDA(dtm, k = 4, control = list(seed = 1154))
#list of words with topic of belonging and probabilities
topics = tidy(lda, matrix = "beta")
> topics
```

```
# A tibble: 9,808 x 3
   topic term                 beta
   <int> <chr>               <dbl>
 1     1 —wouldn't       1.19e- 18
 2     2 —wouldn't       2.96e- 96
 3     3 —wouldn't       2.90e-  4
 4     4 —wouldn't       1.41e- 97
 5     1 'irrationality' 1.78e-106
 6     2 'irrationality' 5.04e-109
 7     3 'irrationality' 1.28e-102
 8     4 'irrationality' 3.00e-  4
 9     1 'watched'       2.15e-  4
10     2 'watched'       8.78e- 95
# … with 9,798 more rows
#top 10 terms
top.terms = topics %>%
group_by(topic) %>%
#dplyr function that returns 10 terms that are most common within each topic.
top_n(10, beta) %>%
ungroup() %>%
arrange(topic, -beta)
#plotting
top.terms %>%
mutate(term = reorder(term, beta)) %>%
ggplot(aes(term, beta, fill = factor(topic))) +
geom_col(show.legend = FALSE) +
facet_wrap(~ topic, scales = "free") +
coord_flip()

#list of sentiment words
library(tidytext)
library(dplyr)
library(syuzhet)
#turning tdm in a tidy df
tidy = tidy(tdm)
sentwords = tidy%>%
inner_join(get_sentiments("bing"), by = c(term = "word"))
> sentwords
# A tibble: 909 x 4
```

```
   term      document count sentiment
   <chr>     <chr>    <dbl> <chr>
 1 difficult 1            1 negative
 2 like      1            1 positive
 3 love      1            1 positive
 4 passion   1            1 positive
 5 prefer    1            1 positive
 6 wonder    1            2 positive
 7 enjoy     2            1 positive
 8 good      2            1 positive
 9 like      2            4 positive
10 work      2            3 positive
# … with 899 more rows

#partition between positive and negative words
table(sentwords$sentiment)
negative positive
    283     626

#plotting most frequent sentiment words with their contribution
library(ggplot2)
sentwords %>%
  count(sentiment, term, wt = count) %>%
  ungroup() %>%
  filter(n >= 10) %>%
  mutate(n = ifelse(sentiment == "negative", -n, n)) %>%
  mutate(term = reorder(term, n)) %>%
  ggplot(aes(term, n, fill = sentiment)) +
  geom_bar(stat = "identity") +
  ylab("Contribution to sentiment") +
  coord_flip()

#sentiment polarity
#afinn lexicon scores
afinn = get_sentiment(dataset$incident,method="afinn")#punteggio
afinn = as.data.frame(afinn)
sum(afinn)
[1] 1495
#bing lexicon scores
```

```
bing = get_sentiment(dataset$incident,method="bing")#punteggi

bing = as.data.frame(bing)

sum(bing)

[1] 633

#nrc lexicon

nrc = get_nrc_sentiment(dataset$incident)

#barplot

barplot(sort(colSums(prop.table(nrc[, 1:8]))),horiz = TRUE, cex.names = 0.7, las = 1,
main = "Emotions in Tweets", xlab="Percentage",col=rainbow(8))
```

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EXECUTIVE SUMMARY

Introduction

The widespread phenomenon of the Internet of Things (IoT) represents a new phase in the Internet revolution emerged in the Information Technology field that, over the last decade, has led to a total paradigm shift in the world of computing and communication. The Internet of Things (IoT) brings the intelligence of the Internet to physical products, known as *Smart Objects*. New business opportunities have also emerged by integrating these technological objects into the development of new services, the so-called *Smart Services*. Even if the idea of connecting objects to each other and to the Internet is not new, the phenomenon of the Internet of Things (IoT) has grown fast in the latest years. Smart objects can be considered as building blocks of the Internet of Things (IoT). They are seen as radical and revolutionary transformation of the original product and smart services as a new way of benefiting from traditional services: they are both perceived by customers as something different and new. Therefore, given the main characteristics of smart objects and smart services and the intense impact they have on customers' live, they can be considered not only as simple innovations but even as disruptive innovations. However, the process of innovation diffusion and its success do not have to be taken for granted. As a matter of fact, the slow pace of customer adoption of new technologies is one of the biggest issues in the Internet of Things (IoT) industry. Most of new smart products and services, once launched on the market, fail. Therefore, understanding which are the factors that cause both customers' innovation adoption and innovation resistance in the specific IoT context is critical to develop and market successfully new products and services, since it has significant implications for businesses. For this purpose, this study proposes two methods of analysis: *sentiment analysis* and *content analysis*. These respectively quantitative and qualitative approaches to textual analysis aim at interpreting and understanding the information contained in the dataset composed of 156 interviews, collected by applying the Critical Incident Technique (CIT). The objective is to extract valuable insights in order to provide a greater clarity on the nature of the factors of innovation adoption and innovation resistance in the specific IoT context and to identify, quantify and classify customers' emotions towards such innovation.

Chapter I - The Internet of Things (IoT)

The Internet of Things (IoT) can be defined as a new phase in the Internet revolution, in which the interconnection of objects around us, the interaction between them and humans as well as the continuous exchange of data will become more and more common in our lives as to become a fundamental part of it. This revolution has emerged in the Information Technology field and has led to a total paradigm shift in the world of computing and communication. The Internet of Things (IoT) concept was introduced for the first time by Kevin Ashton, a member of the Radio Frequency Identification development (RFID) community, in 1999 (Aggarwal et al., 2012). In the following years, the research in this field has continued enabling to create a solid literature base (Vermesan et al., 2014). The Internet of Things (IoT) can be thought as an open and comprehensive network of intelligent and distinctively addressable intelligent physical objects, commonly known as *Smart Objects*. Smart objects are "*physical embodiment with communication functionality, possessing a unique identifier, some basic computing capabilities and a way to detect physical phenomena and to activate actions having an effect on physical reality"* (Hsu & Lin, 2016, p. 516). They are enhanced with computing and communication technology that enable them to join the communication framework and to interact and communicate both with people and other smart objects (Hsu & Lin, 2016) on "*an ongoing basis by sending and receiving data through the Internet that are then stored and organized in a database"* (Hoffman & Novak, 2015, p. 14). Their functioning is based on three fundamental components: "sensors", "actuators" and a "network connectivity". In summary, smart objects are able to: (1) collect, aggregate and analyse a significant amount of data, (2) interact and communicate with each other and with humans and (3) activate actions instantaneously and autonomously (Mani & Chouk, 2018). The data collected, once aggregated and analysed accurately, provide multiple benefits to companies in every field. For example, they could gain a better understanding of their customers and deliver more relevant and personalized offerings (Ostrom et al., 2015). The degree to which an object is considered "smart" depends on its agency, autonomy and authority capacity. New business opportunities have emerged by integrating these technological objects into the development of new services, known as *Smart Services* (Wünderlich et al., 2013, 2015).

Applications and opportunities to use the Internet of Thing are numerous and diverse (Patel et al., 2016). They can be extended to almost every aspect of every-day life of individuals, companies and society as a whole, improving the quality of lives in many different sectors and environments (Atzori et al., 2010, Rose et al., 2015, Patel et al., 2016). Literature has divided the IoT applications into two macro-categories: the first one relating to the human sphere (*consumer segment*) and the second one relating to the business world (*business segment*). The main applications belonging to the first segment are: connected homes, wearables, connected cars and personal health. With regard to the business segment, it is important to mention the following innovative solutions: retail, smart utilities and energy, industrial IoT (IIoT), healthcare and smart city (GrowthEnabler, 2017). Literature also classifies the environments in which these advanced smart solutions can be applied into the following four domains (Atzori L. et al., 2010): *transportation and industrial IoT domain (IIoT), healthcare domain*, *smart environment domain* and *personal and social domain*.

Even if the idea of connecting objects to each other and to the Internet is not new, the phenomenon of the Internet of Things (IoT) has grown fast in the latest years driven by a convergence of various advanced technologies with new emerging computing and connectivity trends and the development of three important related phenomena, namely Big Data, Machine Learning and Cloud Computing. The main drivers of this Internet revolution are (Rose et al., 2015): the development of an ubiquitous connectivity, the widespread adoption of IP-based networking, computing economics, the miniaturizations of technological and communication components and the advances in data analytics. As a matter of fact, in the latest years, smart products and smart services are growing steadily with applications in different domains (Mani & Chouk, 2018). Based on Cisco's market research in 2003 there were less than one device per person (0.8), in 2010 this number grew to 1.84, driven by the rapid development of smartphones and tablets, and it is expected that by 2020 there will be 6.58 devices per person. Based on the forecasts of *Business Insider Intelligence* by 2026 there will be more than 64 billion devices connected to the Internet, with consumers and companies spending around $15 trillion over them, their solutions and supporting systems.

Chapter II - Theoretical framework: *A literature review on customer resistance to innovations in the Internet of Things (IoT) Era*

Rogers (1995, p. 11) defined innovation as "*an idea, practice or object that is perceived as new by an individual or other unit of adoption."* Even if Rogers (2003) has assumed that all innovations are good and should be adopted by everyone since they are improvements of existing products or service substitutes (Ram, 1987), a large majority of them, once launched on the market, commercially fail (Gourville, 2006).

In this context, marketing literature has identified two research paradigm that explain customer response to innovation (Laukkanen, 2016): *innovation adoption* and *innovation resistance.*

2.1 Customer Adoption of Innovation

Adoption can be defined as "*the acceptance and continued use of a product, service or idea"* (Sathye, 1999, p. 325). The theoretical foundations to explain user innovation adoption and, thus, how it spreads in the market were provided by Rogers (1995) with the development of the *Diffusion of Innovation Theory*. For the process to begin, the individual has to be aware of the new product or service (Sathye, 1999). It does not involve all the social system simultaneously: some people adopt the innovation earlier than others do. Therefore, based on their different level of resistance to innovations (personal innovativeness) (Johnson et al., 2018), innovation adopters can be grouped in five categories, namely *innovators, early adopters, early majority, late majority* and *laggards*. According to the Diffusion of Innovation Theory (Rogers, 1995), there are five main adoption factors (or innovation characteristics) that directly impacts on customer adoption decision: *relative advantage, compatibility, complexity, trialability* and *observability.* In 1986, Davis introduced the *Technology Acceptance Model (TAM)* as an adaptation of Fishbein and Azjen (1975)'s *Theory of Reasoned Action (TRA).* In the TAM, Davis (1989) considered two new adoption factors that influence potential adopters' attitudes, intentions and computer usage behaviour: *perceived usefulness* and *perceived ease of use.*

2.2 Customer Resistance to Innovation

Customer resistance to innovation can be seen as a particular form of resistance to change (Ram, 1987), defined as "*any conduct that serves to maintain the status quo in the face of pressure to alter the status quo* and *is associated with the degree to which individuals feel themselves threatened by change*" (Ram, 1987, p. 208). Over the past years, multiple definitions of innovation resistance have been provided. Roux (2007) defined it as a situational attitude manifested through opposition to a situation perceived as dissonant. Ram and Sheth (1989) defined it as "*the resistance offered by consumers to an innovation, either because it poses potential changes from a satisfactory status quo or because it conflicts with their belief structure"* (p. 6). Resistance plays a critical role in determining the commercial success or failure of any innovation, since it can delay or completely obstacle the adoption. For this reason, it has been considered as one of the major reasons for market failure of new products or services (Ram & Sheth, 1989). Resistance can manifest itself in three different ways (Kleijnen et al., 2009; Szmigin & Foxall, 1998), namely *rejection*, *postponement* and *opposition.* Ram and Sheth (1989) argued that innovation resistance exists on a continuum and varies in degree. Therefore, they have distinguished three forms of innovation resistance: *passive resistance*, *active resistance* and *very active resistance.* Over the years, researchers have used the theoretical foundations on the concept of innovation resistance to develop models that could explain this particular consumer response.

2.3 Customer Resistance to Innovation: *Theoretical models*

2.3.1 *Model of Innovation Resistance (Ram, 1987)*

In 1987, Ram introduced the Model of Innovation Resistance, based on the assumption that customer resistance is caused by three categories of determinants: *Perceived Innovation Characteristics, Customer Characteristics* and *Characteristics of Propagation Mechanism*. In the first category of determinants are grouped all the main characteristics of innovation that have been previously identified in literature and that, according to Ram (1987), are relevant to explain customer resistance. Rogers (1962) has identified five main innovation characteristics: *relative advantage*, *compatibility,* *complexity, trialability* and *observability.* Subsequently, Zaltman et al. (1973) suggested some other features that are particularly relevant in the context of innovation resistance: *reversibility, realization, amenability to modification* and *effect on adoption of other innovations*. Ram (1987) grouped these characteristics into two categories: *Customer Dependent Features* and *Customer Independent Features*. According to Ram (1987), resistance to innovation also depends on customers' particular psychological traits. In the context of innovation, the most relevant customer characteristics that have been identified are: *personality, attitudes, value orientation, previous innovative experience* (Brandner & Kearl. 1964), *perception, motivation* (Zaltman & Wallendorf. 1983), and *beliefs* (Yeracaris. 1961). Lastly, Ram (1987) focused on the role that the mechanisms of propagation play in the context of customer resistance. Robertson (1971) classified propagation mechanisms in two dimensions: the *level of marketer control* and the *type of contact with the customers*. Robertson (1971) highlighted the importance of the characteristic of propagation mechanisms in inducing innovation resistance. The most influential features are *clarity, credibility, informativeness* and *perceived source attractiveness or similarity*.

2.3.2 *Consumer Resistance to, and Acceptance of, Innovation Model (Bagozzi & Lee, 1991)*

In 1991, Bagozzi and Lee built a comprehensive model to describe customer resistance to, and acceptance of, innovations by focusing on the particular stage of customer information processing with regard to innovations. Specifically, they structured it as a purposive behaviour process, framed with two decision activities (*goal setting* and *goal striving*), in which one's personal traits and the situation influence the processing of information about an innovation. According to the two authors (1991), the cognitive schema one develop to achieve a goal and the overall goal significantly affect customer decision to adopt or reject an innovation. They also suggested that it is critical to focus on both customer resistance and acceptance and the ways they are integrated during the decision-making process. An important contribution to the literature on customer resistance is the emphasis they gave to the role played by emotions.

2.3.3 *Consumer Resistance to Innovations Model (Ram & Sheth, 1989)*

Ram and Sheth in 1989 built a theoretical model to explain customer resistance to innovation. This model was based on the assumption that individual tend to resist novelty because it threats their satisfactory status quo and established routines with a potential change and because a new product may conflict with their prior belief structure. The two authors identified five customers' adoption barriers and grouped them in two categories: *functional barriers* and *psychological barriers*. Functional barriers arise when customers perceive that by adopting the innovation, they would experience a significant change. These barriers deal with three areas: product usage patterns, product value and risks associated with product usage. *Usage barriers* arise when an innovation conflicts with an individual established routines, habits or existing workflows. Specifically, the higher the changes in individual's routine caused by the innovation, the higher the resistance it will encounter (Herbig & Day, 1992). *Value barriers* deal with the customer perceived value of the innovation and whether the new product or service is better than existing offering to induce customer to replace them (Ferreira et al., 2014). Specifically, if the innovation does not offer a better performance-to-price ratio than the product substitutes, it would encounter a high resistance. *Risk barriers* are defined by Dowling and Staelin (1994) as "*consumer's perceptions of the uncertainty and adverse consequences of buying a product (or service)"* (p.119). Specifically, the higher the risk perceived, the higher the customer resistance (Ram & Sheth, 1989). It is possible to list four main risks: *physical risk*, *economic risk, social risk* and *functional risk*. *Security risk, privacy risk* and *perceived health risk* have also been identified by literature as important driver of customer resistance to innovations. Psychological barriers, instead, relate with the conflict the innovation creates with customer's prior beliefs. These barriers deal with two main factors: the traditions and norms of individuals and the perceived product image. *Tradition barriers* arise when customers perceive that the innovation threats their culture and tradition and it is incompatible with their existing value, past experiences and social norms. The greater the deviation from established traditions required by the adoption of an innovation, the greater the resistance it will encounter. *Image barriers* arise in relation to an unfavourable innovation image the customer perceives due to association between the innovation identity and its origins (product class, industry or country of manufacture). The image barrier can be considered as an extrinsic cue that influences customer's assessment of a new product (Bearden & Shimp, 1982). As a consequence, if customers negatively perceive the extrinsic cue, they will develop a negative image and this will create a barrier (Ram & Sheth, 1989).

2.4 Customer Resistance to Innovation: *Studies in the Internet of Things (IoT) context*

In the existing literature on resistance, Ram and Sheth's model (1989) is the theoretical framework that has received the greatest consideration and through its extensions (Mani & Chouk, 2018) and applications (Mani & Chouk, 2017; Laukkanen et al., 2007; Laukkanen, 2016) it has been possible to obtain interesting results relative to the Internet of Things (IoT) context, specifically with regard to the drivers of customer resistance towards smart products and smart services.

2.4.1 *Mani & Chouk (2018)'s Model*

Mani and Chouck (2018) developed a conceptual model to explain customer resistance to innovation in the smart service context by using Ram and Sheth's model (1989) as theoretical foundation. They adapted Ram and Sheth (1989)'s model to the digital age, investigated customer resistance from an ideological perspective and recognized the relevance of dispositional variables by including three new types of barriers: *technological vulnerability barriers* (technology anxiety, technological dependence), *ideological barriers* (skepticism) and *individual barriers* (inertia). Technological vulnerability barriers is a new category of psychological barriers. Vulnerability can be defined as a state of helplessness, loss of control and dependence (Baker et al., 2005). This state is enhanced as the importance of technology grows in our society leading to negative emotions, technostress, technophobia and much more (Shu et al., 2011). Anxiety and dependence are among the most impactful technological emotions. Therefore, according to Ram and Chouk (2018), technology vulnerability barriers are mainly driven by the perception of technological dependence and technology anxiety; this negative feeling can give rise to psychological barriers that discourage customer adoption. Ideological barriers arise from an individual personal conviction related to a set of negative ideas about an innovation that conflicts with their beliefs and values. This situation leads customers to become skeptical toward the benefits of the new technology (Kleijnen et al., 2009) and, thus, to resist adoption. Skepticism refers to individual tendency to doubt, question and disbelieve (Bunge, 1991). Individual barriers enable to explain the individual predisposition to resist change (Heidenreich & Handrich, 2015; Kleijnen et al., 2009). Polites and Karahanna (2012) associated this tendency to the concept of inertia, defined as the individual predisposition to prefer the status quo rather than going through uncertain changes (Mani & Chouk, 2018). They argued that when individuals are satisfied with their status quo, they also tend to be satisfied with the current products or services and, therefore, they will be less likely to substitute them with an innovation.

2.4.2 *Other relevant studies*

Ram and Sheth's (1989) model have found evidence in Mani and Chouk (2017) research aimed at identifying the main drivers of active customer resistance towards smart objects. Specifically, they conducted their study on French "digital natives" and investigated about the smartwatch. The two authors identified seven resistance drivers grouped in two categories. *Usefulness, novelty, price* and *device intrusiveness* can be classified as product characteristics that cause functional barriers. *Self-efficacy, dependence* and *privacy concerns* can be classified as customer characteristics that cause psychological barriers. Laukkanen (2016) used Ram and Sheth (1987)'s model as theoretical lens to investigate the factors influencing customer adoption, postponement and rejection behaviour toward the Internet and mobile banking service innovation and extended the model by adding demographic variables (age, gender and income). He tested three models in which the dependent variables are: mobile banking adopters versus non-adopters, mobile banking postponers versus rejectors and Internet banking postponers versus rejectors. Lastly, Hsu and Lin (2016) studied the impact of network externalities and privacy concern in the IoT usage.

2.5 Contribution of the research

This research aims at providing a greater clarity on the nature of the factors of adoption and resistance towards the Internet of Things (IoT) innovations. Specifically, the main contribution of this study is to examine customers' reasons to adopt and to reject any kind of smart object and smart service and to identify, quantify and classify customers' emotions towards such AI embedded innovations by conducting a *sentiment analysis* and a *content analysis* on a textual dataset collected through interviews.

Chapter III – Methodology

3.1 Text Mining, Opinion Mining and Artificial Intelligence (AI)

Nowadays, millions of data are generated every minute, driven by the increasing number of users that can access the Internet all over that world and by the advances of the Internet of Things (IoT). On the basis of how they are organized, data can be classified in three different categories: structured, semi-structured and unstructured. However, in the recent years, with the development of Big Data, most of data collected are unstructured. Specifically, almost the 80% of the data generated globally is in unstructured text. It is widely recognized that meaningful and valuable customer insights can be extracted from an accurate analysis of these data. Therefore, companies able to organize, analyse and extract relevant information from their database can achieve a significant competitive advantage. However, the use of traditional techniques on unstructured databases could be time consuming, expensive and highly demanding in terms of work required. To overcome these issues, text mining techniques represent an efficient tool to automatically process a large amount of unstructured, natural language text, extract high quality and accurate information and find interesting patterns to support strategic decision making. It is by using text mining that organizations can go deeper and analyse vast amount of contents in order to understand what customers think and feel about them and their products. For this purpose, sentiment analysis is one of the most used text mining technique (Liu, 2012). Opinion mining, also called sentiment analysis, is a type of natural language processing, defined as the area of study that focuses on developing methods that can automatically detects, extracts and analyses sentiments, emotions, opinions, evaluations, attitudes and appraisal about an "opinion target", like a product, a service, a business, an individual, an event, an issue, a topic and much more expressed in digital forms on social media platforms (Liu, 2012; Vinodhini & Chandrasekaran, 2012; Varathan et al., 2017). Sentiment analysis metrics are used to categorize text according to the following criteria: the polarity of the sentiment expressed through the opinion (positive, neutral or negative), the polarity of the outcome, the level of agreement with a topic, whether the news is good or bad, support or opposition attitudes and, lastly, pros or cons opinions (D'Andrea et al., 2015). Understanding and classifying opinions brings considerable benefits in almost every domain. Among the major applications it is worth to mention government intelligence, business intelligence, competitive intelligence and marketing. However, all of this could not be possible without the application of Machine Learning and Natural Language Processing (NLP), two of the major subfields of Artificial Intelligence (AI) that refers to the ability of machines to learn from experience, optimize their performance by adjusting to new input on a continuous basis and simulate human intelligence by thinking and acting like humans to increase the possibilities to achieve a desired goal.

3.2 Critical Incident Technique (CIT)

The Critical Incident Technique (CIT) is a qualitative inductive grouping method (Hunt, 1983) that enables to collect rich narrative information about a construct of interest in order to explore it and obtain useful insights about the frequency or the existence of patterns of factors within the phenomenon investigated and classify it in different categories (Woolsey, 1986). In this study, the CIT procedure was applied to collect narrative data through interviews with the research objective to investigate and gain understanding of the Internet of Things (IoT) phenomenon, specifically customers' reasons to adopt and reject any IoT innovation and the polarity and polarity intensity of the emotions expressed. The "critical incident", or event, respondents had to describe was about a recent opportunity in which they had the possibility to purchase a product with built-in AI and/or to use a service with built-in AI but they did not purchase/use it or they eventually decided to purchase/use it. Then, they were asked what was the product or service, the reasons that led them not to buy/use or to buy/use the product or service and what they felt and thought during the episode.

3.3 Dataset

The data collected by applying the CIT technique were organized in a dataset composed of 10 information categories (variables) and 156 interviews of which 86 describe episodes of innovation adoption and 70 describes episodes of innovation resistance. The subsequent step was a data cleaning process: 8 information categories considered as not relevant for the research objective were discarded and the remaining two were combined together. The resulting dataset is the focus of the subsequent analysis. It is critical to specify that, for research purposes, the positive and negative interviews were combined together to perform the sentiment analysis but they were kept separated to conduct the content analysis.

3.4 Bag of Words (*WordCloud*)

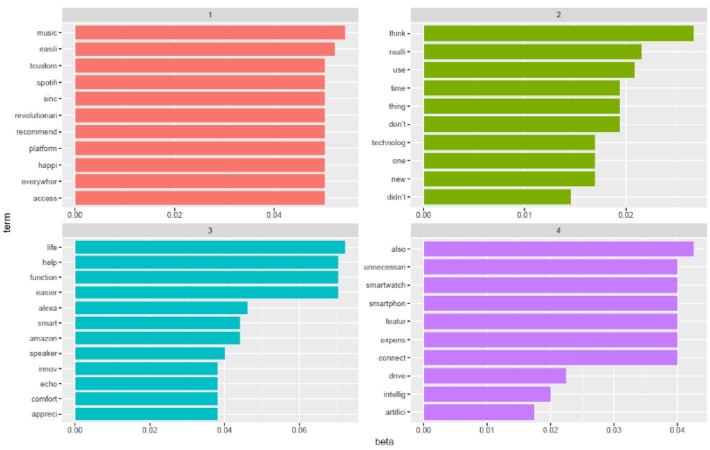
The Bag of Words (BoW) model is textual representation and analysis that enables to extract specific features from text document. These features are first organized within a textual corpus and then within a two-dimensional matrix. In this study, each interview is transformed into a vector of numbers that can be used as an input (or output) for machine learning algorithms.[63] The model focuses on whether and how many times a specific word is present in the document regardless of its position and each word count is considered as a feature. First, the collection of 156 interviews was converted into a corpus that was pre-processed in order to uniform the characters, remove punctuation and numbers, remove stopwords and activate the stemming process. The pre-processing phase led to the development of a *WordCloud* (see Fig. 3.1). It is a representation of the most frequent words, that are "Alexa", "Like", "Home", "Artificial", "Time", "Amazon", "Assistant", "Useful", "Intelligence", "Technology", "Device", "Google" and "Buy". The next step consists into the creation of a matrix, named “tdm”, by using the TermDocumentMatrix() function. The resulting matrix contains 156 documents (interviews) and 2542 terms with 97% sparsity. In this contingency table, the first entry represents the list of terms, also known as the vocabulary of all the unique words that appear in the entire collection, while the second input corresponds to the interview number and each matrix value (cell) indicates the frequency of occurrence of the specific term in the interview. The frequency value of each word was then used as a feature to implement the Topic Modeling.

Fig. 3.1. WordCloud

3.5 Topic Modeling Method

The Topic Modeling Method is an unsupervised machine learning technique aimed at detecting hidden structure in a collection of documents.[64] Specifically, with the Latent Dirichlet Allocation (LDA) approach it is possible to discover latent topics, associate them to the identified topics and finally use the calculated association to organize and interpret the textual data. Starting from the DocumentTermMatrix, the transposed of the BoW matrix, the algorithm computes the probability of belonging *per-topic-per-word* β, which is the probability *b* that that a specific term is generated from a given

Fig. 3.2. 4-topic LDA Model



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[63] Browniee, J. (2017). *A Gentle Introduction to the Bag-of-Words Model.* In Deep Learning for Natural Language Processing. Available at: https://machinelearningmastery.com/gentle-introduction-bag-words-model/ [accessed 10/05/20]

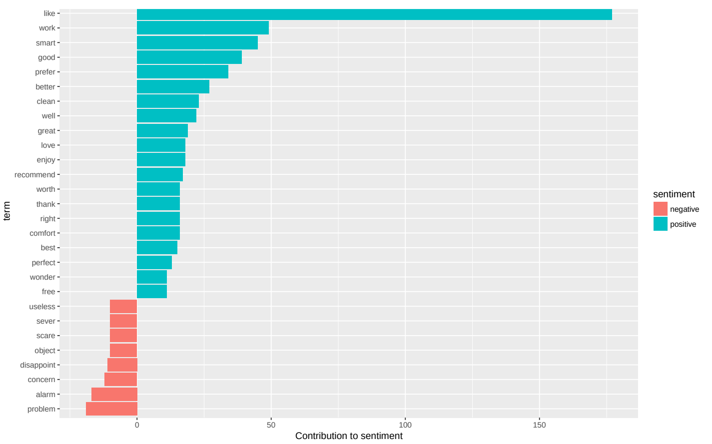
[64] *Monkeylearn.com:* https://monkeylearn.com/blog/introduction-to-topic-modeling/ [accessed 06/06/20].

topic. Fig. 3.2 illustrates four topics that have been generated by using the 10 most common terms within each of them. The most common words associated to topic 1 suggest that the topic discussed is “Spotify”, a subscription-based digital music service. The most common words associated to topic 2 suggest that the topic discussed is “time saving”, which is one of the main advantages that these innovative technologies have in common. The most common words associated to topic 3 suggest that the topic discussed is “Alexa”, the virtual digital assistant developed by Amazon. The most common words associated to the fourth, and last, topic suggest that the topic discussed is the “Smartwatch”, a smart mobile device with a touchscreen display designed to be worn on the wrist.

3.6 Sentiment Analysis

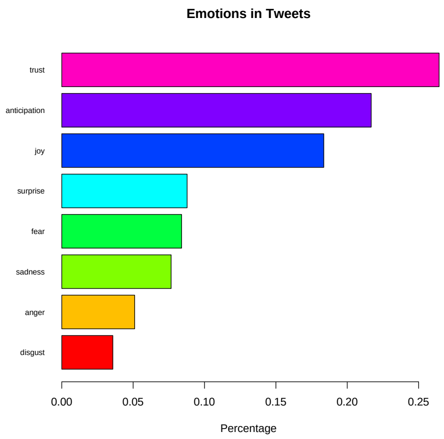
The sentiment analysis is performed on the dataset described above in order to detect the general polarity and polarity strength toward any smart product and smart service. First, by using the tidytext package, it was possible to obtain a complete list of *sentiment words* contained in the interviews with their related frequencies, in order to have an overall idea of the polarity of the collection. Fig. 3.3 provides a clear representation of the sentiment words used in the interviews. Specifically, it enables to quickly identify which word contributed the most to positive or negative sentiment. This impact is measured simply by considering the frequency of occurrence of the term (value placed on the ordinate axis in Fig. 3.3). The most common positive sentiment words shown in Fig. 3.3 are “like”, “work”, “smart”, “good” and “prefer”, while the most used negative sentiment words are “useless”, “scare”, “disappoint”, “concern” and “problem”. We can observe that the positive sentiment words are greater in number and appear more frequently that the negative sentiment ones, thus suggesting the overall polarity of the collection of interviews.

Fig. 3.3. List of terms with that contribute the most to the sentiment



After having classified the sentiment words and identified their relative frequency, the focus is on measuring the polarity intensity and classifying the sentiment, by assigning a score to each interview through specific functions of the syuzhet package. Three sentiment lexicons were used in this study, namely “afinn”, “bing” and “nrc”. The “afinn” lexicon assigns a score of -5 to negative words and a score of +5 to positive words. The “bing” lexicon assigns a score of -1 to negative words and a score of +1 to positive words. The “nrc” ” lexicon does not assign any score, since it only classify the sentiment words in eight sentiment categories. By inserting one of the three available lexicons in the syuzhet package as input to the get_sentiment() function, to each term in the comments vector of the interviews is given a score according to the criteria of the specific lexicon chosen. Subsequently, by algebraically summing up the scores assigned to the words of each single interview, a total sentiment value, which measures the polarity intensity, is obtained for each of them. The *barplot* in Fig. 3.4 shows the distribution of the eight emotions provided by the "nrc" lexicon within the corpus of interviews. In particular, the abscissae axis indicates the percentage of the interviews characterized by the specific emotional class listed on the ordinate axis. As the "nrc" lexicon reports a prevalence of positive feelings within the collection, even cumulating the scores assigned to the words that make up each individual interview, according to the "afinn" and "bing" methods, gives a value of overall sentiment absolutely positive and equal, respectively, to 1495 and 633. In conclusion, although the three lexicons provide different results in an absolute sense, they reveal the same trajectory in terms of polarity.

Fig. 3.4. Sentiment Distribution Barplot



3.7 Content Analysis

Content analysis (CA) is a research methodology dealing with the content and the meaning of a text, often unstructured (Gheyle & Jacobs, 2017). This study approaches content analysis in a qualitative way with the aim to investigate and identify inductively, from the dataset presented above, the most discussed reasons to resist and to adopt any kind of AI innovation. The interesting results emerged are illustrated in the subsequent sections.

3.7.1 *Reasons for IoT Innovation Resistance*

Desire to Maintain Control over Habits: artificial Intelligence (AI) tools, with their multiple functions and features, do ordinary and effortless tasks that individuals are always being used to accomplish on their own. Therefore, the adoption requires changes in established routines and behaviours. This is associated to the concept of *pervasiveness*. From the analysis emerged that individuals enjoy and feel comfortable in performing these activities and, therefore, they tend to resist the possibility that a device could replace them. They also have expressed concerns about a possible loss of control over their life and time. Thus, individuals resist adoption to prevent that any aspect of life could be regulated and managed by technology. This barrier resulted to be particularly relevant for usage decisions of systems like Alexa and Siri, two virtual assistants developed respectively by Amazon and Apple.

Lack of Perceived Usefulness: from the content analysis conducted emerged that smart devices' functionalities can easily be performed by individuals without any technological support and with little effort. Therefore, the absence of perceived usefulness, which refers to the benefits the customer thinks will receive from the use of the device, resulted to negatively impact customer adoption decision specifically towards smart systems such as the smartwatch, Amazon Echo, an intelligent speaker that can be controlled by voice thanks to Alexa's assistance, and Siri. In summary, these devices are perceived as useless and as not having any additional advantage especially if the user has a smartphone or a computer.

Perceived Price: from this study emerged that the price is considered a barrier for three main reasons. First, these devices are mainly perceived as useless with low economic benefits. This barrier arises especially for devices like the smartwatch and the smart speaker, since they are perceived as mere "gadget" and futile objects. Second, to work effectively and exploit all the functionalities, it is required that multiple devices are connected to each other and the installation, repair and maintenance of the entire system is very expensive. Third, devices like Amazon Echo and the HomePod, applications like Waze, systems like Siri are perceived as being not sufficiently developed. Therefore, they do not meet user's expectations in terms of quality and individuals resist adoption and prefer to wait for advanced and improved versions.

Functional Risk: in this study, the functional risk resulted to be particularly relevant in shaping customer adoption decision. It is related to the performance uncertainty that arises from the concern that the device could not function properly. Specifically, it emerges in regard to home appliances, like the refrigerator or the washing machine with AI integrated.

Preference for Human Interaction: in this study, the need for human interaction resulted to be particularly impactful for adoption decisions. In the service context, respondents reported a preference for the traditional store. Furthermore, they reported that the questions one ask to devices like Alexa could be the source of spontaneous conversations between members of the same family. Therefore, individuals are concerned that, in the future, these conversations will no longer take place among people and will be replaced by simple commands imposed by humans to electronic devices. For this reasons, individuals prefer to preserve the traditional human interaction alive as long as possible rejecting the usage and adoption of these technologies.

Privacy Concerns: evidence from this analysis shows the privacy's critical role in shaping user's intention to adoption, due to the IoT technology ability to collect and manage a huge amount of personal data and information. Specifically, the loss of control over personal or private information, the possible improper access and unauthorized secondary use resulted to be the main cause of privacy concerns. Smart devices like Google Home and Alexa have the microphone always turned on and could potentially listen and record whatever happens at home. This increases users' perception of being *"subtly listened",* controlled and observed. Customers need to perceive they have a certain degree of control over their personal data and the idea of sharing them with unknown sources makes them feel uncomfortable. These concerns create a huge psychological barrier that leads to innovation resistance.

Network Externalities: network externalities can be defined as "*the value or effect that users obtain from a product or service that will bring about more value to consumers with the increase of users, complementary products or service"* (Katz & Shapiro, 1985). It is associated to the concept of perceived complementarity, defined as "*the availability of function or applications serving to fill out or to complete IoT services"* (Hsu & Lin, 2016, p. 519). From this study emerged that perceived complementary has a significant impact on perceived benefits that, in turn, contribute to predict attitudes towards the adoption and usage of IoT innovations. This resulted to be particularly relevant for smart speakers. Indeed, in order to completely exploit, take full advantage and enjoy all their functionalities and potentials, they need to be part of a "smart home". However, creating such a smart ecosystem is both complex, expensive and time-consuming since it would imply radical changes in the house furniture. For this reasons, most of respondents reported to have postponed or rejected the adoption.

Complexity/Ease of use/Self-efficacy: Perceived complexity deals with the difficulties in using and understanding the new technology (Kleijnen et al., 2009). It is related to the concept of perceived ease of use. From the analysis of the interviews, the high perception of innovation complexity resulted to be a significant barrier to adoption. Specifically, with regard to AI-built innovation, it arises mainly because creating a smart environment at home requires to substitute all the old not connected objects with the new ones. A number of respondents reported to have difficulty in understanding how these devices work and in installing and connecting them. Furthermore, they have to download many apps and connect them to Alexa, for instance. All of these practices are perceived as complex, time-consuming and challenging. The amount of cognitive effort required is perceived as higher than the expected benefits. This can also be associated to the concept of *self-efficacy*. Indeed, findings demonstrates that it is critical for customers to perceive that they are able to understand how these devices work. All of these factors emerged as significant reasons cons the adoption and use of smart systems.

Vulnerability (Anxiety and Dependence): vulnerability is related to the concept of technological dependence and technology anxiety. This study evidenced the relevance of these psychological states in shaping customer adoption decision in the IoT context. Specifically, they mainly derive from the perceived possible negative effects of machines on people related to the feeling of isolation and addiction that is originated from the use and abuse. Technology makes people feel connected but more “physically distant” and alone. Respondents reported that technology is also perceived as a source of stress that threat their freedom and makes them feel oppressed. They are concerned of loosing their “human” nature and the contact with reality. Most of them feel uncomfortable when interacting with machines due to the fear of being manipulated. These perceptions give rise to significant psychological barriers that discourage customer adoption.

Skepticism: skepticism towards the IoT devices promised benefits emerged as a significant psychological barrier. What respondents questioned the most is devices actual usefulness and performance effectiveness. They prefer to rely on their personal abilities and efforts due to a lack of trust in the innovation outcome.

Negative Perceived Image: four negative images emerged from the analysis. First, smart devices are perceived as mere “gadget” and futile objects. Second, they are considered “trends” destined to become obsolete soon. Third, they lack perceived added value. Fourth, they are associated to the concept of laziness.

3.7.2 *Reasons for IoT Innovation Adoption*

Time Saving: this is one of the most discussed AI innovation advantages. Movie streaming services suggest users alternatives on the basis of their personal tastes. Roomba, an autonomous robotic vacuum cleaner, has brought a help to all those people who cannot spend a lot of time cleaning the house. Service chat with artificial intelligence helps users find solutions to their problems, make orders and obtain quick answers by simply interacting with it. Amazon provides suggestions on what could be interesting for the user thus reducing the time needed to search on the website. In summary, all of these advanced technologies represent a concrete help for those who, for any reason, have no time to perform these activities enabling a significant time saving.

Recommendation System: movie and music streaming services use artificial intelligence to “learn with experience” enabling users discover new contents that best fit their profiles. This feature is considered by respondents as a significant advantage and a source of satisfaction, loyalty and increased time usage.

Make Life Easier: one of the most discussed advantage of AI innovation is their ability to make user’s life easier and more efficient by simplifying all the daily activities. This feature is making AI an essential component in life.

Unconstrained Access and Use: though the Internet connection, most of AI systems can be accessed or activated everywhere in every moment of the day enabling users to enjoy their contents and their functionalities without constrains. From the analysis emerged that these features positively impact on customer's decisions to adopt such AI innovations.

Perceived Usefulness: due to their multiple features and functionalities, smart devices are perceived as highly useful and it positively affects attitude and intention in the usage and adoption of such AI innovation.

Human Traits: users feel attracted and fascinated in interacting with an intelligent machine that is programmed to think, speak and act as a human. They treat these devices as a real person, they enjoy to see how a robot handles different situations and requests and remain surprised for their efficient performances. Furthermore, some respondents reported that, due to their human characteristics, interacting with such machines makes them feel comfortable and not alone. They are also considered a source of entertainment even in social situations with other people, like family members or friends.

Conclusion

This thesis adopted a quantitative and qualitative approach to textual analysis and examined all the results with respect to the research question in order to provide a greater clarity on the nature of the factors of innovation adoption and innovation resistance in the specific IoT context and to identify, quantify and classify customers' emotions towards such innovation. For this purpose, after having introduced the Internet of Things (IoT) phenomenon and having provided the theoretical tools to comprehend the concepts of customer innovation adoption and customer innovation resistance by reviewing the most relevant academic contributions in this fields, two methods of analysis were applied, namely *sentiment analysis* and *content analysis*. The findings emerged could particularly benefit companies. The diffusion and success of most of smart products and services do not have to be taken for granted. Indeed, one of the biggest issue in the Internet of Things (IoT) industry is the low pace of customer adoption of new technologies. Therefore, understanding which are the factors that cause both customers' resistance and adoption in the specific IoT context is critical to develop and market successfully new products and services. These insights could help firms reduce innovation failure and increase the adoption rate. Future research could focus on the investigation of innovation adoption and innovation resistance factors by taking into account demographic variables (age, gender and income) of respondents. In addition, a more in-depth analysis could be conducted on specific smart products or smart services in order to identify for each of these the perceived strengths and weaknesses.