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Consumers and IoT: a qualitative analysis of factors pro and against the smart objects' adoption

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ACADEMIC YEAR 2019-2020

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Introduction

The digitalization of the physical world occurred with the advent of the Internet of Things, has consecrated the entrance of human beings into the "fourth industrial revolution", characterized by fast and revolutionary innovations. Indeed, the Internet of Things allows the connection to the Internet of physical objects equipped with sensors, which thus become "smart" and anthropomorphised, able to listen, communicate, capture and transmit information to the outside world. The relationship between humans and objects has therefore changed compared to the one with traditional objects, as individuals no longer relate to passive entities, but interact with active and autonomous devices.

The ability of smart objects to capture information from the external environment and transmit it to other devices, renders them an important source of "Big Data", i.e. data that individually have no value, but analysed in large volumes by Artificial Intelligence systems allow to extract patterns and strategic insights about consumers, necessary for business decisions. In addition to the benefits for companies, the advantages provided by IoT have increased its ubiquity across many different sectors, so that today we can observe applications of this technology in the field of human health and productivity, in offices, homes, factories, shops, cities and in the daily life of individuals.

The enormous impact of IoT and its ability to create value for the various stakeholders involved, has always permitted positive predictions about its growth by scholars. These forecasts, however, have found evident limits and difficulties in their occurrence: if in 2015 Ibm estimated 1 trillion connected devices in 2020, the reality of the facts recorded 18.4 billion in 2018, and the expectations for 2023 are oriented on decisively lower numbers (29.3 billion). Although the growth of IoT continues to be positive over the years, the number of objects connected to the Internet remains inferior to the previous estimates and the potential of this phenomenon, and the failure rate of innovative products remains high. One of the primary causes of the slowdown in the adoption of these Innovations is the consumers resistance to the adoption of smart devices, which is the main topic of this study.

In light of this, the previous literature has investigated the adoption of Innovations mainly in a positive way, focusing exclusively on the drivers that positively influence the evaluation of a new product, assuming that the negative factors were the exact opposites and specular of the positive ones ("Complementary Assumption", Sutton). From this emerges the need to analyse the barriers of resistance implemented by the consumer as a category in itself, independent by the positive factors of adoption of smart objects, in order to verify the relationship and the possible correspondence between these two.

Therefore, the present research focuses on the role of the consumer, analysing the positive and negative drivers that influence the process of adoption of AI devices. The categorization of positive and negative factors will be carried out with a qualitative method through the use of the Critical Incident Technique.

The study of the relationship of these drivers has led to relevant conclusions, proving the existence of factors of adoption (resistance) to these devices that are not polarized, i.e. that act only unidirectionally, not presenting their negative (positive) opposite. In other words, it emerges that the reason why individuals decide to reject a smart device is not always the exact opposite of the reason that drives them to adopt it: for example, it was found that the “Privacy” drives only negatively the adoption of devices, since there is no positive specular factor that leads consumers to perceive “protection” of their personal data.

In Chapter I the economic and technical overview of the Internet of Things will be presented, with the aim of introducing the phenomenon of analysis and highlighting both its potential value and the limitations in the smart objects adoption registered in recent years.

In Chapter II the analysis of the previous literature on the diffusion and adoption of innovative products will be conducted. The main models will be investigated, highlighting the major drivers of adoption and resistance already identified by scholars.

In conclusion, Chapter III will be totally dedicated to data analysis: after an overview of the qualitative method and the Critical Incident Technique, the adoption and resistance categories and the relationships between them will be described and commented.

Chapter I

IoT and Smart Objects: the New Frontier

In this Chapter, a technical and economic overview of the Internet of Things will be conducted in order to introduce the topic of my analysis.

In the first section, I will provide a brief excursus on the birth of the Internet and IoT.

In the second one, the innovation of IoT will be examined in-depth, with specific reference to smart objects. Traditional objects have become, thanks to the Internet connection, devices able to capture data from the environment and exchange it with the outside world. These objects are therefore anthropomorphized, acquiring the ability to listen, communicate and transmit information. These and other features typical of smart objects, as well as a variety of benefits that will be discussed extensively throughout this Chapter, will lead to an inevitable change in the relationship between consumers and traditional objects. Furthermore, the specific role of Artificial Intelligence (AI) and Big Data will be analysed, clarifying the meanings of these two concepts and the relationship between the two, IoT technology and smart objects.

The third section will provide an analysis of the IoT market whose value will be explained through an analysis of the growth factors of the sector, the major fields of application of this technology and the stakeholders involved. My study will provide an overview of the social, cultural and political relevance of the topic, highlighting the potential for value creation in the various sectors.

To conclude, the study will focus on the limitations found in the propagation of IoT technology: despite the enormous value created by this innovation, the growth of the sector, although positive, is slower than was expected in previous years. Compared to its enormous potential, there are factors that are slowing down its growth, leading to limitations in the adoption of smart products both by companies and individuals.

This introductory framework is preparatory to the second Chapter, where I will examine the main drivers to adoption and barriers of resistance to Innovations identified by previous literature, at the end of which I will formulate the research question.

1.1 The Evolution of Internet and the Birth of IoT

By defining the Internet of Things as the "digitisation of the physical world" (McKinsey Global Institute, 2015), it is possible to perceive its potential for radically changing the way human beings typically interact with their surrounding environment. Before the advent of the Internet, the primary human need to socialise and communicate was traditionally satisfied through traditional unmediated models (i.e. face to face relationships). The first transmission of data between two distant computers occurred in 1969, although the birth of the Internet is commonly recognised with the creation of the TCP and IP protocols in 1974, which officially defined the rules for transferring data packets among computers.

The advent of the World Wide Web in 1989 introduced the HTML network, and the creation of the first search engines such as Google and Wikipedia occurred. Internet evolution has been fast and moved rapidly to the Web 2.0 Era, in which more sophisticated forms of communication were developed (i.e. social networks such as Facebook) allowing many-to-many interactions.

Currently, we are in the Post-Social phase, also known as Internet of Things (IoT). The expression "Internet of Things" was first coined in 1999 by the British researcher Kevin Ashton who during a presentation at P&G introduced the possibility of connecting to the Internet any object or device equipped with sensors for the first time. The IoT phenomenon is defined by many as the new frontier of the Internet, since "*it brought the intelligence of the Internet to physical products, with the potential for something new to emerge*" (Hoffman et al., 2015). It is a disruptive digital transformation that leads us towards the so-called Industry 4.0, defined as the "fourth industrial revolution". The concept of "cyber-physical systems" was introduced in order to differentiate this new evolutionary phase from the previous one, characterised by electronic automation (Gartner Press Release, 2015). According to this, Forbes described the IoT Era by highlighting the fundamental role of machine-learning algorithms, which have enhanced robotics, computers and equipment connected to the Internet (Charles Towers-Clark, 2019).

For the first time, conventional objects are now connected to the Internet, leading to significant implications for different actors including first and foremost firms, marketers and consumers. By maintaining my research focus on the role of consumers, the introduction of IoT has had a twofold consequence: on the one hand, it has changed the way they have always used the Internet, since technology has now pervaded every moment of people's daily lives; on the other hand, their relationship with traditional objects has been thoroughly altered, as objects are now "devices" connected to a network that enables them to interact with people, and acquire and transmit data to the outside world. Indeed, IoT is an unprecedented innovation, due to its capacity to transport the digital into the real world and vice versa: the extension of the Internet network to real objects and places allows the interconnection of everyday objects, which become "smart" and able to communicate both with human beings and with each other, sharing data and accessing aggregated information (Magrassi et al., 2002).

1.2 Smart Objects, AI and Big Data: A Technical and Economic Overview

Commonly, smart objects are intended as "*everyday objects and products that are able to communicate with other objects and consumers, through the Internet*" (OECD, 2015). IoT technology has significantly changed the way individuals used to conceive traditional objects: thanks to a network connectivity (Bluetooth, Wi-Fi, RFID and so forth), objects are now able to collect, analyse and transmit data detected from a certain environment, communicating with each other and working as a whole assembly-line.

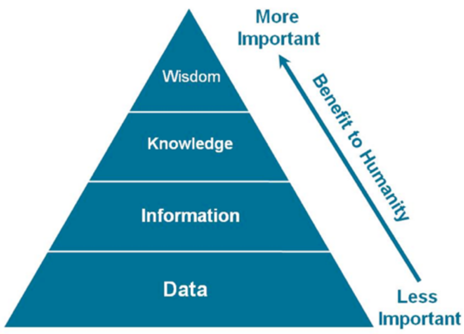
In technical terms, smart objects are "*items equipped with a form of sensor or actuator, a tiny microprocessor, a communication device, and a power source*" (Vasseur et al., 2010). The sensor or actuator enables smart objects to interact with the external world: this is used in order to sense physical factors, ranging from easy-to-measure properties such as humidity and temperature, to more complex phenomena such as pollution, the presence of other cars and so on. The microprocessor allows to transform the data captured, providing the device with the necessary computational power to make it "smart"; the communication device enables the smart object to communicate its sensor readings to the outside world and receive input from other devices; the power source provides the electrical energy to work (Vasseur, 2010). An object is defined "smart" to the extent of its ability to exercise agency, autonomy and authority. Agency is the capacity to affect, and be affected by, other entities (Franklin et al., 1996), autonomy is the capacity to function independently (Parasuraman et al., 2000), and authority is the capacity to control other entities and make decisions for them (Hansen et al., 2007). The degree of these three properties in a specific object determines how effectively "smart" it is. Generally, it is possible to notice a wide spectrum of possible degrees of smartness: for instance, analysing the two extremes, on the one hand, there are objects with a low degree of autonomy that require human intervention at various points for an action to succeed; on the other hand, there are devices with a high level of agency and autonomy that are able to behave authoritatively, making and executing decisions independently, without human intervention (Parasuraman et al., 2000). It is precisely due to agency, autonomy and authority that smart devices are innovative in comparison to traditional non-smart objects. The concept of "Innovation" has been defined by Peter F. Drucker as a "*change that creates a new dimension of performance*". Indeed, a product is perceived as innovative by consumers to the extent to which it improves their performance, increasing the efficiency and/or effectiveness. John Seely Brown added that "*beyond innovation lies disruptive innovation, which actually changes social practices – the way we live, work and learn*". In this sense, the author highlights the change brought about by the innovation that forces consumers to adopt new habits, change traditions and values, moving from their status quo and comfort zone. Additionally, Rogers (1995) defined Innovation as "*an idea, practice or object that is perceived as new by an individual or other unit of adoption*". According to Rogers, the concept of "Perceived Novelty" by consumers is decisive for a product to be defined as innovative. Therefore, it is possible to conclude that smart products can be perceived by consumers as a great novelty compared with conventional ones (Ram, 1987). Among the various characteristics that render them innovative, there are certainly "Intelligence", "Ubiquity" and "Connectivity" (Mani et al., 2016). These three features allow smart devices to: 1) exchange information with the external environment thanks to communication protocols, 2) act independently from the human being, basing their actions on data previously captured by sensors, 3) be connected to other objects and devices, so that they can be used by consumers without limits of place and time. Moreover, a key feature that derives from the high degree of Connectivity and Autonomy of smart objects is the so-called "Interoperability", defined by the Cambridge dictionary as "*the degree to which two products, programs, and so on can be used together, or the quality of being able to be used together*". Interoperability has been recognised by McKinsey's research as a significant variable in the value creation of IoT products: in fact, the report shows that 40% of the total potential value generated by IoT technology can be unlocked only if numerous IoT devices work together. In numbers, Interoperability is necessary to allow IoT technology to impact the economy with more than $4 trillion per year in 2025. The many definitions given to Interoperability concord on the two necessary and sufficient conditions for a system to be interoperable (Diallo et al., 2011): the first condition is the possibility to exchange information between the parts forming the system; the second condition is the usability and usefulness of the information, which is usually determined by the device that receives the information. IoT systems consist of several components (devices, communication, services, applications and so on), each of which includes the concept of Interoperability. As this research will maintain its focus on consumers, I will refer to Interoperability solely between smart objects. Thus, the ability of different smart products to cooperate and communicate effortlessly with each other enables everybody to realise the full potential of an IoT ecosystem: on the one hand, companies may create new alliances and synergies by making their devices communicate; on the other hand, consumers will see their objects increase in value, as interconnecting them will increase their functions and perceived usefulness.

In light of the features already discussed, it is evident that smart objects differ from traditional ones because of their degree of anthropomorphization: due to their ability to communicate, listen, transmit and process data, they embody a disruptive innovation, representing something more than passive entities that consumers invest with meaning (Belk, 1988). Being able to interact and communicate with inanimate devices that possess human senses leads to consistent changes in the relationship between consumers and objects, perfectly reported by the famous caption "*on the Internet of Things, nobody knows you are a fridge*".

Continuing the analysis of IoT phenomenon and focusing on a communication perspective, according to the Cisco Internet Business Solutions Group (IBSG), IoT is simply the point in time when more "things or objects" are connected to the Internet than people (Cisco IBSG, 2011). Basically, IoT technology is leading the traditional communication to a new frontier, changing its nature and actors. In fact, nowadays there are several forms of interaction ranging from the more traditional Consumer-to-Consumer (C2C) and Consumer-to-Machine (C2M) to the new Machine-to-Machine (M2) and Machine-to-Physical (M2P). In conclusion, it is evident that the ability of smart objects to interact can be exercised with or without the consumer being present, confirming the above-mentioned feature of Autonomy. Therefore, smart objects must be understood as partaking in a broader assemblage that does not always involve the direct interaction of the object with the consumer (Hoffmann et al, 2018).

By emphasising the crucial role of communication and information sharing for human evolution over time, it is compelling to briefly examine how human beings process data through the analysis of the data-information-knowledge-wisdom (DIKW) hierarchy (Ackoff, 1989). By looking at the pyramid below (Fig. 1), the distinction between data and information, often used as synonyms, becomes evident: data is the raw material present in the environment and perceived through human senses, i.e. a set of facts, symbols and figures. Individual data by itself has no value, but volumes of it can be helpful to identify patterns. Differently, information can be understood as data processed and organised considering the context and the belonging category, with the purpose of providing more usefulness (Ackoff, 1989). Usually computers deal with data, while human beings deal with information, knowledge and wisdom. In fact, by giving meaning to information and by assembling it together, we move on to knowledge: it represents information of which a person is aware, that has been understood and employed for something useful. At the top of the pyramid there is wisdom, which is the possession of knowledge used to make smart connections between different phenomena and patterns, necessary to understand principles and mechanisms that govern data behaviour.

Figure 1



Source: Cisco IBSG, April 2011

From the Ackoff model, it is possible to conclude that everything begins with the data collection. In fact, there is a positive correlation between input (data) and output (wisdom), since the more data is created, detected and analysed, the more knowledge can be obtained. Therefore, the incredible importance of data for human beings and the crucial role of their communication and sharing becomes noticeable.

Nowadays, human beings have numerous tools to collect and process data as a result of the technological and digital progress. Indeed, Artificial Intelligence (AI) is defined as the "*system's ability to correctly interpret external data, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation*" (Kaplan et al., 2019). This concept, apparently similar to the one of IoT technology, is actually quite different: Kaplan et al. (2019) have specified that, considering the Internet of Things as the phenomenon according to which smart objects are equipped with sensors and software to capture and transmit data, the last-mentioned is merely a single source of information for AI systems. Hence, Big Data is a distinct concept from IoT, as the latter is only one of the many inputs towards Big Data (Lee, 2017), which gather data and information from many other sources (such as company databases, social media, etc.). The difference between normal Big Data and IoT Big Data is that the latter is more

heterogeneous and fast-growing, since it is a continuous flow of information collected through sensors and smart objects (Marjani et al., 2016). Hence, even though they embody different concepts, IoT has introduced unprecedented new opportunities and tools to collect data from the external environment in any type of industry. In fact, nowadays IoT applications in various fields represent the major sources of Big Data.
To better comprehend the relationship between IoT and Big Data, it is necessary to analyse the key characteristics of the latter. In fact, Gartner has defined Big Data as "*high-volume, high-velocity and/or high-variety information assets that demand cost-effective, innovative forms of information processing that enable enhanced insight, decision making, and process automation*". Similarly, Tech America defined Big Data as "*a term that describes large volumes of high velocity, complex and variable data that require advanced techniques and technologies to enable the capture, storage, distribution, management, and analysis of the information*" (TechAmerica Foundation's Federal Big Data Commission, 2012). According to these definitions, it is important to analyse the so-called "Three V's", which are the three dimensions introduced by Laney (2001) that properly describe the nature of Big Data:

- "Volume" relates to the huge amount of information that AI systems are able to support, contrarily to traditional technologies. Human beings generate a massive amount of data every day that are captured by different devices through sensors. The major peculiarity of these data is that analysing them individually is neither useful nor significant, but when aggregating large volumes of data it is possible to uncover patterns among them, which can create value and provide important insights to companies.
- "Variety" refers to the heterogeneity of the dataset to be analysed. In fact, data are divided into structured (tabular data found in spreadsheets or relational databases), unstructured (images, theses, sounds, videos and other multimedia content that do not present the organisational structure required by the analysis machines) and semi-structured (a middle way between the two; these are not strictly in accordance with the standards of analysis, such as the "Extensible Markup Language" (XML), which is a textual language for exchanging data on the Web). For datasets to be efficient, it is important to present a high level of variety: to get significant insights, companies use to collect unstructured data both from the outside (social media and so forth) and from the inside (through their own devices and sensors). Moreover, in order to exploit these different types of data within the business process, firms need to analyse them with appropriate technologies and machines. For instance, on the one hand facial recognition technologies enable retailers to acquire insights about store traffic, customers characteristics, and their in-store movement trends; on the other hand, social media allow marketers to analyse in depth consumers' preferences and opinions about products. The analysis of these two different sources of information is leveraged in strategic decisions related to product personalisation, promotion and placement.
- "Velocity" deals with the data rate generation and consequently the speed at which companies should analyse them. The proliferation of digital devices used daily by individuals, such as smartphones and

sensors, has led to an unprecedented rate of data creation and is driving a growing need for real-time analytics.

Over the years, other Three V's were introduced to complete the descriptive framework of Big Data:

- "Veracity" is a term coined by IBM, which describes the inherent unreliability of some sources of data. In fact, in addition to reliable and accurate data, a large amount of data that are not certain, but still provide valuable information (such as sentiment analysis in social media), are produced every day. Therefore, it is necessary to have instruments capable of decoding and analysing the latter since, according to the dimension of Variety described above, the more varied the analysed dataset is, the more relevant the insights are.
- "Variability" and "Complexity" were introduced by SAS, the former is related to variations in the data generation flow rates, since usually data Velocity is not consistent over time; the latter refers to the wide amount of Big Data sources, which requires to be connected, matched and cleaned before completing the analysis.
- "Value" was introduced by Oracle, defines the relatively low-value density of Big Data. As a matter of fact, data in their original form usually have a low value related to their volume. However, a high value can be obtained by analysing large volumes of data, as similarly mentioned when discussing the volume feature.

The advent of Big Data and AI systems has revolutionised the world of technology and data analysis, creating a real digital revolution. The forecast for the Big Data market is certainly positive, since it is expected that in 2025 the total amount of data created by devices all over the world will reach 175 Zetabytes. Considering that nowadays 50.1 Zetabytes of data are generated, the growth of this industry will be fast in the coming years, which demonstrates the significance and ubiquity of the phenomenon. For a better understanding of the units of measure we are talking about, it is necessary to consider that 1 Terabyte contains the amount of data entering 1500 CDs, enough to store about 16 million Facebook photographs. Taking into account that Facebook processes up to 1 million photographs per second (Beaver et al., 2010), and that 1 Petabyte = 1024 Terabyte, Facebook stores 260 billion photos using storage space of over 20 Petabytes. Therefore, given that 1 Zetabyte corresponds to 1 billion Terabytes, the immensity of the data estimated by the above-mentioned forecasts becomes evident (Barnett, 2016).
From a managerial point of view, Big Data major value resides in the high-volume analysis used by marketers to support strategic decision-making processes. In order to make such evidence-based decision making, organisations need efficient methods to turn high volumes of fast-moving and heterogeneous data into significant insights. The process of extracting information and finding patterns from Big Data can be divided into two main parts (Labrinidis et al., 2012):

- Data management: includes the necessary stages to acquire and store data, preparing them for analysis. Explicitly, these are the phases of acquisition, cleaning, integration, aggregation and representation of data;
- Data analytics: refers to the techniques and models used to analyse data and acquire useful information. Specifically, it includes the phases of data modeling, analysis and interpretation.

To conclude, in order to fully benefit from IoT, firms need to install platforms and machines that are able to store, manage and analyse a vast volume of data in a scalable and cost-effective manner, with the aim of converting it into valuable insights for their business (Ahmed et al. 2016).

1.3 IoT Market Analysis: Growth Factors, Main Application, Stakeholders and Limitations to Adoption

"*Trying to determine the market size of the Internet of Things is like trying to calculate the market for plastics, circa 1940. At that time, it was difficult to imagine that plastics could be in everything. If you look at information processing in the same way, you begin to see the vast range of objects into which logic, processors, or actuators could be embedded*"
Prof. Michael Nelson, Georgetown University.

The rapid growth of Internet of Things (IoT) over the years allows to make positive predictions about its future evolution. The global IoT market was valued at US$ 190.0 Bn in 2010 and it is projected to reach US$ 1,102.6 Bn by 2026, exhibiting a CAGR of 24.7% in the forecast period (Fortune Business Insight, 2019).

Smart objects have become an inevitable part of people's daily lives, and this is demonstrated by IoTs adoption rate, which is positive for both businesses and individual consumers. In fact, in 2014 14% of companies were using this type of technology, while in 2019 the business adoption rate has grown to 25%. As a matter of fact, individuals in their daily lives are being always more connected: considering that in 2003 there were approximately 6.3 billion people in the world and 500 million devices connected to the Internet, there was less than one (0.08) device per person. In that year, there were a small number of connected objects to the network, also because ubiquitous devices such as smartphones were just being introduced (Apple launched iPhone in 2007). The market launch and the fast growth of smartphones and tablet PCs raised the number of devices connected to the Internet to 12.5 billion in 2010, and the world's human population increased to 6.8 billion, making the number of connected devices per person more than 1 (exactly 1.84) (Evans, 2011). In 2017, people owned an average of four IoT devices per person that communicated with the Cloud. Globally, 127 new devices connected to the Internet are estimated every second (Petel et al., 2017). Moreover, the total number of devices connected worldwide is expected to rise to 75.44 billion by 2025, about five times the amount of connected devices in 2015, which was 15.41 billion (Statista Research Department, 2016).

McKinsey Global Institute estimated that IoT could have an annual economic impact of $3.9 trillion to $11.1 trillion by 2025 across many different fields (including factories, cities, retail environments, and human health) (Manyika et al., 2015).

1.3.1 Growth Factors

Various factors are contributing to the positive sign of the Internet of Things market growth. First of all, the concept of "Connectivity": over the last years, many resources have been allocated in order to improve the infrastructures that enhance connectivity between devices located in different areas. For instance, LPWAN (low-power wide-area network) is a wireless network covering a broad area and allowing long range communications between connected devices, characterised by low costs and low power requirements. An example of LPWAN are smart metering devices (such as smart gas meters, street lighting systems and so forth), which are battery-operated devices capable of working up to 10 years in complete autonomy, without any human intervention. Considering that in 2017 only 20% of the global population was covered by this kind of network, a significant growth has been predicted for the coming years: an annual increase of 30% is expected from 2016 to 2022, which will lead to 100% of the population covered by LPWAN network in 2022. In addition, Connectivity is expected to benefit from the introduction of the 5G network, which will have an improved performance due to the increased bandwidth, allowing new applications for innovative IoT experiences such as Virtual and Augmented Reality. As evidence of the growth, McKinsey has estimated that investments in IoT technology are projected to rise 13.6 % per year through 2022.
Moreover, the general technological progress occurred in recent years is another important growth factor of IoT market. The phenomenon of Innovation is mostly measured by technological progress: this refers to the application of scientific findings to the technological sector by improving existing products or creating new ones, enabling companies to increase their efficiency by entering new markets or reducing production costs. As far as IoT is concerned, technological progress has led to a sophistication of the devices (that are now functioning better and with a lower power requirement) and a decrease in the associated production costs. This has allowed the development of more integrated IoT solutions: the so-called "easy-to-use" IoT devices have been developed in order to ensure that businesses and consumers are not prevented from adopting them because of their complexity. Thus, by lowering sales prices and increasing ease of use, it has been possible for a large number of companies and individuals to benefit from IoT technology, enabling the growth of the entire industry. An example of what has just been said are the LIDAR (Laser Imaging Detection and Ranging) sensors, which are laser-based devices able to determine the distance of an object in the surrounding environment, essential for autonomous driving. The price of LIDAR sensors has decreased 65 times in the last ten years and is expected to decline further from 2020 to 2030 ("Lidar 2020-2030", 2019). The substantial price decrease, in conjunction with the increasing sophistication of LIDAR technology, is allowing the development of fully autonomous cars, which are expected to account for 25% of the total number of vehicles purchased by 2035 (Petel et al., 2017).
Finally, a further growth factor for IoT industry is the potential of already existing traditional IT devices.

Although they have a moderate growth rate (around 2% per year), these devices cover a significant market share (more than five billion smartphones, two billion personal computers, and one billion tablets in the world). The possibility of connecting such a large number of already existing devices (for which there is no need to sustain any production cost) to IoT technology is a great opportunity that fosters the growth of the entire industry (Dahlqvist et al., 2019).

1.3.2 IoT Application Fields

Due to all the factors listed above, growth perspectives for IoT technology are considerable. Nowadays, the ubiquitous connectivity network of smart devices has paved its way into our daily lives, being applied in different sectors in the real world such as military defence, medicine, industry, agriculture, energy, smart cities, homes and so forth. In order to properly understand the magnitude of IoT phenomenon, the actual value creation and the benefits provided, it is necessary to analyse the fields of application of this technology from a horizontal point of view. To do so, I have decided to follow the McKinsey Global Institute report "The Internet of Things: Mapping the Value Beyond the Hype" edited in 2015, in which has been analysed how IoT creates real economic value. The evaluation of the economic impact of IoT applications has been determined considering both the potential benefits that can be generated by this technology – including productivity improvements, time savings, and improved asset utilisation – and an approximate economic value for reduced disease, accidents, and deaths.
McKinsey highlights a crucial point: business-to-business (B2B) IoT applications can create more value than pure consumer applications. While consumer applications – such as smart watches' fitness monitoring and self-driving cars – attract the greatest public attention also due to media coverage, word-of-mouth and observability, the prediction is that B2B uses can generate nearly 70 % of potential value enabled by IoT. Bearing these concepts in mind, McKinsey has identified nine settings in which IoT technology creates value (considering environments such as homes, offices, factories, workplaces, retail environments, cities, vehicles, outdoors and human health), of which I will analyse the most relevant ones:

- **Humans**: IoT services have been successfully applied in various sectors in the human field. The first one concerns human health, since the ever-increasing number of objects integrable with intelligent sensors are making it easier to connect medical devices to the network for monitoring parameters. The major advantages are firstly in the area of prevention and ease of monitoring (and consequently have a crucial impact on the social system); secondly in the sector of emergency assistance in case of accidents and need for *ad hoc* diagnosis. Among the several applications in the health field, we may mention:
  - Organ-on chips: these microdevices can replicate organ and tissue functions, by reproducing cellular structure and physiology. They enable the immediate measurements of the organ functions and their endurance. These devices have varied applications in the field of drug testing and discovery as well as defence research projects (Balijepalli et al., 2017);
  - Digital and 3D Pills: these are characterised by in-built chips that record the effects of a drug on a specific individual and transmit these data to the experts (Ventola, 2014);

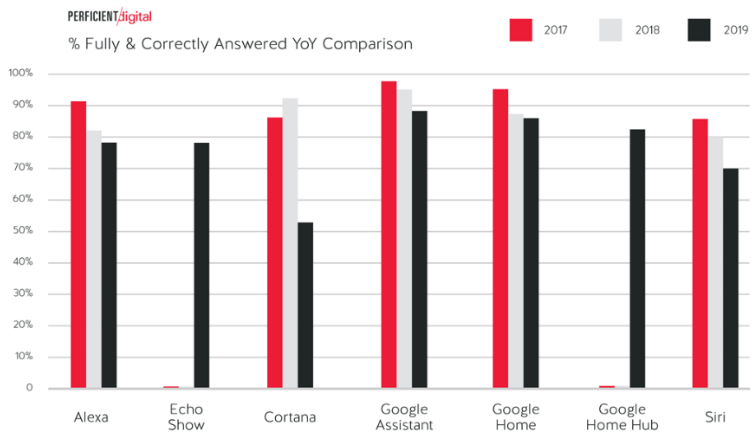
- Smart Wheelchairs: have been created to reduce the dependency of handicapped people. Their primary aim is to decrease the amount of effort required to navigate the wheelchair intelligently by using the collaboration of sensors, Artificial Intelligence and IoT (Desai et al., 2017);
- Wearable: a disruptive product category of devices that measure, monitor and analyse daily human activity and vital statistics. Among these, smart watches are certainly the most appreciated wearable devices by consumers: these are watches that, thanks to the Internet connection, on the one hand are able to monitor the physical activity of the individual, on the other they substitute the mobile phone in its basic activities of calling, sending emails and messages.

Various benefits are provided to individuals by this kind of smart objects, of which the most relevant are: an increased patient adherence to prescribed therapies; a better management of emergency cases (such as heart attacks); a more efficient interoperability among devices (thanks to End-to-End connectivity that allows a more effective data transfer); a reduction of unnecessary medical visits and consequently of the costs of assistance (Della Peruta, 2011).
In general, the application of IoT technology to the human health sector could have an economic impact of $170 billion to $1.6 trillion per year in 2025. Moreover, it could enable benefits for society worth more than $500 billion per year (considering the improved health of users and the reduced cost of care for patients with chronic diseases).
Furthermore, human productivity has been strongly impacted by IoT technology. This sector requires the use of Augmented and Virtual reality devices capable of redesigning projects with greater efficiency and effectiveness. An example of the helpfulness of this technology in workplaces are the goggles that can display data to guide workers' performance. Google has already introduced "Google Glasses" for enterprises: they are glasses that internally have tiny wearable computers which would present information floating in the workers' field of vision, allowing them to refer to the correct procedure without having to find a computer terminal.

- **Home**: among the myriad devices that have contributed to making our homes "smart", the Voice Assistant is certainly the best known among consumers. The reason why smart assistants have so much hit the market is the implementation of the "voice recognition" feature: due to the voice computing, individuals are now able to connect to the Internet with the sole use of their own voice, without any keyboard, screen or mouse (Oreskovic, 2020). These devices, thanks to advances in Artificial Intelligence, can answer any question, control individuals' smart home, suggest recipes, read news, check the weather, and complete any other basic task individuals may have in mind.
The first voice assistant introduced to the market in 2010 was Siri: this is an app integrated into iPhones, which is able to recognise the commands spoken by individuals and carries out simple tasks such as sending messages, calling someone, making reminders and setting calendar appointments. Siri has been soon overtaken by its main competitor, Google: Google's voice assistant is much more accurate in

responses and has a better voice recognition. In the figure below is reported the comparison of results of a test conducted on the accuracy of voice assistants' answers in 2017, 2018 and 2019:

Figure 2



Source: Perficient digital

Interestingly, from the chart above, it is possible to observe that last year (2019) every personal assistant dropped in accuracy to some degree. These data indicate that current technologies may have reached their maximum capabilities peak, and the next big smart assistant's upgrade will likely require the creation of new algorithms.

The 2019 report, on the one hand indicates that Google Assistant still answers most questions and has the highest percentage of requests fully and correctly responded to; on the other hand, Amazon's voice assistant (Alexa) has the second-highest percentage of questions answered accurately (Enge, 2019).

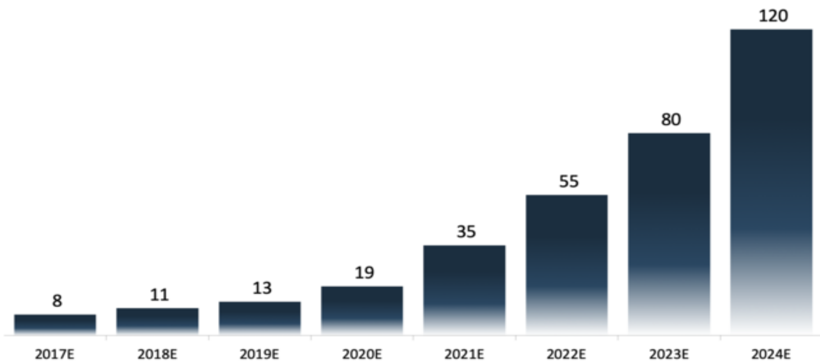
In addition to voice assistants, many other devices have contributed to making our home smart, including:

- Smart appliances: devices such as self-guided vacuum cleaners, dishwashers or refrigerators, which can operate autonomously to complete tasks, drastically reducing humans' workload. The forecast is that chore automation can cut 100 hours of labour per year for the typical household, as it is only necessary to give these machines the start command, and then let them do all the work;
- Security sector: the intrusion detection systems (composed of cameras, alarms, sensors, etc.) detect the condition of windows and doors to prevent theft, break-ins and intruders. IoT in this sector would have an impact of more than $20 billion per year (based on avoided injuries and deaths);
- Energy management: the monitoring of remote-control appliances is made with sensors to efficiently save energy and avoid home accidents. It is the case of connected thermostats, which are expected to save up to 20% of energy. In addition, smart meters are becoming increasingly popular, since they measure energy consumption and transmit data in real time to the energy provider. Accurate analytics enable decision makers to measure the appropriate level of electricity supply that they must provide to customers.

Primarily, McKinsey Institute estimated that IoT applications in the home could have a total economic impact of $200 billion to $350 billion per year in 2025.

- **Cities**: smart cities use IoT devices to collect and analyse data that will be used to increase efficiency by improving public utilities, infrastructures and services.
  Since the 600 largest cities in the world are expected to generate 65% of global GDP growth through 2025 ("Urban World: Cities and the Rise of the Consuming Class", 2012), the impact of IoT is substantial in order to make cities "smart". Authorities are encouraging states to invest in the development of smart cities: first of all, the European Union, in the current European programming 2014-2020, has allocated 456.6 billion euros in funds for projects directly or indirectly related to smart cities (Ansa, 2019).
  Even at a global level, investments in smart cities are showing a positive sign and are expected to continue to grow in the coming years (see Fig. 3).

Fig. 3: Annual Smart City Investment (Global, $)



Source: Business Insider Intelligence estimates, 2019

Some concrete examples of smart cities and innovations developed with IoT are described as follows (Moeia, 2020):

- Amsterdam is developing the city's smart grid and offers solar panels and home solar storage units to households that are connected to it. These batteries help lower the stress on the grid at peak hours by allowing residents to store energy during off-peak hours. Smart grids belong to smart architectures, since they enable enormous savings in terms of energy and resource conservation;
- Paris has introduced a car sharing programme in 2011 called "Autolib", with a fleet of about 3,000 connected vehicles. Cars can be tracked via GPS and drivers can use the car's dashboard to reserve parking spaces in advance;
- London is developing a smart parking project in order to reduce urban traffic congestion. Drivers will be able to quickly locate the car park, eliminating the problem of lengthy searches for a spot;
- Copenhagen records more than 40% of the city's residents who move by bike each day. For this reason, sensors are used to monitor the city bike traffic in real time, providing useful data on the enhancement of cycle routes in the city;

- New York has developed a programme of connected cars in 2015, with the purpose of determining where drivers make frequent hard brakes or sharp turns because of the traffic. Data recorded by sensors can be used to improve road conditions and decrease traffic congestion.

Overall, the estimation is that IoT applications in the cities' infrastructures and services could have an economic impact of $930 billion to $1.6 trillion per year in 2025.

- **Factories**: considering as factories all those environments in which is carried out a standardised type of work, included in this category are agriculture settings, manufacture facilities and processing industries.
  - In the manufacturing sector, by connecting items or containers with IoT devices - smart devices or unique identifiers - it is possible to optimise the production process, monitor machines, and collect useful data to improve logistics. In addition, since items are connected to sensors, it is possible to monitor the status of the object from production to disposal, optimising the entire product lifecycle.
  - In the agricultural industry, it is an increasingly common practice to use IoT technology to ensure the official identification of animals: in this way, the animal's physical state and location can be monitored in real time. Moreover, several other benefits arise from IoT use in agriculture, such as real time monitoring of livestock health, improved irrigation methods, remote soil monitoring, reduced water consumption and streamlining of farming processes (Growth Enabler Report, 2017).

  In the above-mentioned factories, IoT could potentially generate an economic impact of $1.2 trillion to $3.7 trillion per year. The benefits would arise from a series of factors, among them: 10 to 20% energy savings; 10 to 25% potential improvement in labour efficiency; improvements in equipment maintenance, inventory optimisation; workers' health, safety and security.

- **Vehicle:** the vehicle sector is benefitting enormously by the introduction of IoT. In particular, the automotive industry has adopted smart objects – specifically RFID technology – in order to monitor and report real time data in several phases of the chain: first of all, data is acquired by sensors during the manufacturing process and maintenance operations, enabling a new and more effective way to optimise vehicle production and logistics; secondly, smart devices are used to monitor and report every part of the vehicle, from tyre pressure, to location of other vehicles, in order to improve quality control and customer service.

  In addition, new forms of communication are emerging thanks to IoT infrastructures: Vehicle-to-Vehicle (V2V) and Vehicle-to-Infrastructure (V2I) communications will significantly advance Intelligent Transportation System (ITS) applications, increasing vehicle safety services and traffic management. For instance, vehicles will be able to make automatic emergency or breakdown calls when the need is detected, collecting as much data as possible from the surrounding environment, such as the supporting transportation infrastructure (roads, rails and so on), the presence of other vehicles nearby and so forth (Sundmaeker et al., 2010). Correct data analytics in this field can help authorities observe the road history of accidents (the circumstances in which it has occurred, the drivers' speed and so on), reduce the number of road mishaps, determine the moment in which traffic is more congested and study an optimal route plan in order to minimise it. Moreover, analytics can indirectly improve shipment movements, road safety, and end-to-end user experience in terms of delivery time.

To conclude, it is necessary to mention the connected cars category, which are either self-driven or driver assisted vehicles, that fall within the field of automation.

In general, it is estimated that IoT technology applied to the vehicle industry could generate $210 billion to $740 billion per year by 2025.

- **Outside**: sensors and monitors have been applied to the outside environment with the purpose of:
  - Increasing safety and security: wireless identifiable devices are used in order to supervise both environmental phenomena (pollution, earthquakes, forest fires, floods, etc.), and to monitor unforeseen events in buildings (water leaks, gases, unauthorised entry, vandalism, etc.).
  - Improving navigation system: sensors inform advanced navigation systems to improve the routing of ships, airplanes, and other vehicles on the road. They are also used to track containers and packages in transit.

  The economic impact of IoT technology in this industry is expected to be about of $560 billion to $850 billion per year in 2025.

1.3.3 Stakeholders

Numerous stakeholders are affected by the Innovation of the Internet of Things: from organisations to individuals, there are relevant implications that must be considered, as IoT and smart objects create both opportunities and risks for the actors involved.

Above all, those who are directly and indirectly impacted by IoT technology are consumers. As a matter of fact, they capture most of the benefits: McKinsey estimates that the users of IoT could capture 90% of the value that IoT applications generate. As human beings, through their entire life they travel, play sports, stay at home and perform many other activities in fields in which IoT products and services are present, thus being able to fully benefit from them (for instance, the previously discussed self-driving cars, smartwatches, smart appliances for homes, along with others). Therefore, even if companies are the ones investing in IoT, it is customers who fully benefit from it. In fact, the significant market growth discussed above has led to increased competition in IoT market: this has had positive consequences for consumers, as companies are offering products and services of a higher quality, i.e., with better features, improved efficiency and lower costs. However, there is another angle through which we must look at this phenomenon, since there are some associated risks to consumers: first of all, the privacy topic, which is the most contemporary and controversial one. Smart objects, by definition, collect information and real time data from their surroundings through sensors, and transmit them to other devices and entities. The first issue is that there are too many data. The Federal Trade Commission report ("Internet of Things: Privacy & Security in a Connected World", 2015) found that fewer than 10,000 households can generate 150 million discrete data points every day. This enormous amount of data leads immediately to the second issue: the increase of interconnected devices – as we have mentioned above the concept of interoperability – creates more entry points for hackers and cyber criminals and leaves sensitive information vulnerable. In addition, Connectivity allows smart objects to acquire sensitive information from the environment and exchange it with the outside world, even without specific authorisation from the individuals involved. People need to be aware of the amount of personal data that are being gathered about them and how that information is used when they buy a smart object (Insider Intelligence, 2020). Hence, organisations must be transparent with consumers, providing the necessary information about how their data is collected, stored and used, and ensuring that the whole process is appropriately protected. In truth, the risk factors mentioned are just some of the deterrents that can lead consumers to be sceptical of smart objects and consequently reject them, preventing IoT from fulfilling its true potential.

The second subject to analyse consists of IoT user companies, which are firms that have invested in the Internet of Things with the aim of modernising their product or service. The first step for companies is to understand when and how to invest, as it is necessary to have a broad knowledge of the industry in order to make smart investments. The major problem for companies investing in IoT is that, even if their purpose is to get insights about consumers, they often end up with a large amount of data and without the ability to correctly analyse them. In fact, there is evidence that most of IoT data are not currently used: a recent report from MGI has indicated that companies do not analyse most of the data collected by their sensors. For instance, only 1% of data gathered from an oil rig with 30,000 sensors is examined ("The Internet of Things: Mapping the Value Beyond the Hype", 2015). Generally, IoT technologies are not fully exploited by businesses: nowadays data are mostly analysed by firms in order to detect anomalies and control the workflows, rather than being used for marketing purposes, which is the sector that creates the greatest value. In fact, IoT is fully exploited with activities such as consumers' behaviour prediction and personalisation of the offer, allowing companies to take complete advantage of its benefits. The main reason why firms do not fully exploit the analysis of IoT data is the lack of staff able to analyse them correctly. Furthermore, even though hard data are more complete and objective, human beings tend to assign them minor value, since when making strategic decisions they usually prefer to consult other people for advice or to look back on their own experience.

The third stakeholder to be analysed in IoT market is represented by technology suppliers: in fact, IoT components and system market grew 160% in 2013 and 2014, and McKinsey esteemed that this growth could exceed 30% per year through 2025. As the market continues to grow, suppliers need to find ways to distinguish their own business and face competition. For this reason, some IoT suppliers offer distinctive technology, others provide distinctive data, others establish technology platforms and others are specialised in end-to-end solutions. To conclude, it is necessary to mention retailers and marketing departments. IoT technology has strongly changed traditional marketing metrics by introducing systems which provide essential consumers' insights to decision makers. More in-depth, the main marketer task is to analyse consumers' behaviour in order to predict the future, providing consumers with a totally personalised product and experience. To do so, on the one hand, a large number of organisations purchase data from external sources; on the others, there are firms which invest in IoT and analyse their own internal data. The latter solution has shown a higher revenue growth comparing to the former. A strong implication for companies adopting IoT is that, in order to fully exploit its benefits, appropriate knowledge about how IoT systems work is required. Moreover, it is necessary to have the capacity to use data stored in order to drive the strategic decision-making process, as well as the ability to adapt the organisation to new systems and business models.

In addition, the advent of the Internet has radically changed the touch points between consumers and brand, transforming it from a linear to a multi-interface relationship. The introduction of mobile shopping, for instance, allows consumers to buy anything at anytime from anywhere. It leads to a totally different shopping experience from the traditional one: in fact, we talk about Retail 4.0 referring to technological innovation and the digitisation of many shopping habits to build new management platforms through smart technologies.

1.4 Limitations to Adoption

Despite the undoubted importance of mentioning the growth factors, the areas of application of IoT technologies and its main stakeholders in the various fields, it is also necessary to analyse the limits found in the adoption of this technology. The potential of IoT innovation and smart objects has always made scholars forecast very positively: in 2010 Hans Vestberg – at the time CEO of Ericsson – predicted that in 2020 there would be 50 billion devices connected to the Internet; five years later Ibm raised the bar to a trillion connected devices in 2020. Nevertheless, the positivity of these numbers has not been fulfilled over the years, so much so that Ericsson itself lowered its forecast to 28 billion connected devices, including smartphones, by 2021. At the time, Gartner estimated 25 billion devices connected by 2020.

Taking as reference the data contained in the CISCO Annual Internet Report 2018-2023, in 2018 users in the world connected to the Internet were 18.4 billion, and these have been predicted to rise to 29.3 billion by 2023. CISCO Report also states that by 2023 two thirds of the global population will have an Internet connection, with a total of 5.3 billion internet users (66% of the world population) compared to 3.9 billion (51% of the world population) Internet users in 2018. Even though the growth of IoT phenomenon is still positive through the years, clearly the registered numbers of devices connected to the Internet are lower than the initial forecasts, which were too optimistic. The reasons for this discrepancy are multiple. First of all, this can be explained by the very nature of Innovations which, as such, involve a certain degree of risk. When analysing the general context, in fact, it is not uncommon to find on the market the so-called "slow-diffusing innovations": these are innovations which, despite the obvious competitive advantage over existing products, have been slowly adopted by consumers. Some examples of this type of Innovations are the dishwasher – which has taken half a century from its introduction on the market to become a mainstream product–, the microwave oven, the automatic teller machines, online banking and the alternative fuel vehicles (Garcia et al., 2007). It is necessary to understand why Innovations are not immediately accepted by consumers, since slow-diffusing innovations have negative repercussions on the firms introducing them: in addition to creating delays in returns on investment (ROI), they can cause negative paybacks if the product is removed from the market before sales take off. Secondly, the failure of some innovations can be attributed to evident reasons, such as high market prices in the launch phase, the low quality of the product, the low competitiveness compared to competitors, the lack of innovation of the product and the inability of the company to create a niche market, etc. Besides the reasons mentioned above, it is fundamental to regard as one of the primary causes of failure of Innovations the so-called "consumer resistance": individuals reject Innovation when the latter comes into conflict with their habits, belief structures, attitudes, traditions and values, forcing them to significantly change their status quo.

Hence, the focus of my research will be on the role of consumers, and on how they tend to approach the world of IoT and smart objects. This analysis will be conducted in order to identify the main critical incidents driving individuals to adopt or reject smart products, as well as trying to respond to the above-mentioned discrepancy between the great potential of IoT Innovation and its effective use by consumers.

Chapter II

Main Drivers to Adoption and Barriers of Resistance in Previous Literature

Over the years, the topic of the diffusion of technological products has been extensively investigated in order to fully comprehend the consumers' process of acceptance and resistance to Innovation. The purpose of this Chapter is to provide an accurate overview of the previous literature dealing with these themes, maintaining the focus of the analysis on critical incidents which affect consumers' adoption of smart objects.

The first section of this Chapter will deal with the so-called "*literature of adoption*", starting from what is historically considered the leading model of diffusion research, namely the "Diffusion of Innovation Model" (Rogers, 1962). With the aim of providing a complete overview of the innovation adoption drivers identified by scholars in the previous literature, the main models will be analysed considering simultaneously the most important aspects and possible limitations.

The second section of this Chapter will be focused on the "*literature of resistance*", which encompasses the analysis of drivers that form the major resistance barriers identified in previous literature. In addition to the historically recognised barriers to Innovation, new factors recently introduced in the literature of resistance will be examined. These are barriers specifically related to smart objects' nature and features, namely network externalities, privacy concerns and demographics.

At the end of the Second Chapter, the research question will be formulated.

Finally, the Third Chapter will be entirely devoted to data analysis, conclusions and recommendations.

2.1 Literature on Adoption

In this section I will analyse the main models forming the theoretical basis on the themes of diffusion of innovation and which have mostly focused on adoption factors. The fundamental characteristics, theoretical contributions and empirical findings related to smart objects will be explored. Starting from the Diffusion of Innovation Theory (Rogers, 1962) as a milestone of social sciences, the concept of Innovation and diffusion of an innovative product in a social context will be analysed through the identification of the first adoption drivers. Subsequently, the Theory of Reasoned Action (Fishbein and Ajzen, 1975), the Theory of Planned Behaviour (Ajzen, 1991), the Technology Acceptance Model (Davis, 1989) and the User Acceptance of Information Technology (UTAUT and UTAUT2) will be discussed in order to identify the adoption factors that have been introduced by scholars over the years.

To conclude, for a complete understanding of these models, a section will be dedicated to the criticisms and limitations of these theories.

2.1.1 Diffusion of Innovation

Thanks to the Diffusion of Innovation (DOI) Theory developed in 1962, Rogers is recognised as the pioneer of innovation diffusion research.

In his model, Rogers defined diffusion as "*a process by which an innovation is communicated through certain channels over time among the members of a social system*" (Rogers, 1962). According to this definition, diffusion is the conveyance of a new idea among people, highlighting the centrality of the notions of novelty, communication and social system on which his theoretical framework is founded.

It is rather problematic to define the concept of "innovation" precisely. Over the years, many scholars have given different definitions underlining the various aspects of the phenomenon. With the awareness of being unable to provide an exhaustive review here, it will be taken as reference the definition of innovation as "*the implementation of a new or significantly improved product (good or service), or process, a new marketing method, or a new organisational method in business practices, workplace organisation or external relations*" (OECD/Eurostat, 2005). In this definition, the emphasis is mainly on the notion of novelty as an indispensable element for a product to be innovative. Maintaining the focus of the consumer behaviour analysis, Rogers (1962) defines innovation as "*an idea, practice or object that is perceived as new by an individual or other unit of adoption*". According to him, to perceive a product as innovative, the latter must represent a change from the user's initial status quo. The basic premise here is that innovations are by nature positive for the consumer, as providing improvements over substitute products (Ram, 1987, pag. 208). Therefore, it is generally assumed that to be adopted, innovations must somehow improve the consumer's initial situation by increasing its efficiency and/or effectiveness.

By delving into the consumer's mental process of whether or not to adopt an innovation, Rogers defines the innovation-decision process as the sequence of five distinct and yet related "Phases": in the "Knowledge Phase" the individual becomes aware of the existence of an innovation and tries to comprehend its functions and potential benefits; in the "Persuasion Phase" the individual creates a positive or negative attitude towards innovation; in the "Decision Phase" the positive or negative attitude is respectively transformed into the decision of adoption or rejection; in the "Implementation Phase" the individual converts the decision into concrete actions; in the "Confirmation Phase" the individual seeks reinforcements on an already made innovation-decision. The major consequence of the process described above is the decision to adopt or reject the innovation in question.

Considering innovativeness as "*the degree to which an individual is relatively earlier in adopting new ideas than the other member of a system*" (Rogers, 1962), DOI divides individuals into five adopter categories: innovators, early adopters, early majority, late majority and laggards. It is a spectrum of sequential categories that originate from innovators (active innovation-seekers who first adopt the innovation within a system) to laggards (traditional people anchored to the past and old habits, usually risk-averse).

Factors of Adoption

According to DOI Theory, there are five essential characteristics which directly impact the decision-making process to adopt an innovation:

- "Relative Advantage": as mentioned above, this is the degree to which an innovation is perceived as better than the idea it supersedes (Roger, 1962). In order for innovation to spread, it is necessary that consumers perceive something new that makes them choose to abandon the initial status quo, change their usual behaviour and adopt the innovation. It has a positive impact since the more customers perceive the new idea as better and advantageous, the more the adoption rate will increase;
- "Compatibility": is the degree to which an innovation is perceived as being consistent with the existing values, past experiences, and needs of potential adopters (Rogers, 1962). Consistency with social values and culture is the basis of the innovation acceptance. Innovations that are not in line with previously established values and social norms will be accepted more slowly than new ideas supporting the pre-existent culture of a certain society;
- "Trialability": is the degree to which an innovation may be experimented on a limited basis (Rogers, 1962). The possibility of trying an innovation before deciding to adopt it definitively reduces consumer uncertainty and perceived risks, also increasing the individual's confidence with the new idea. Consequently, Trialability has a positive impact on adoption rate;
- "Observability": is the degree to which the results of an innovation are visible to others (Rogers, 1962). Observability of innovation stimulates discussion with other people, word-of-mouth and direct evidence. It is involved in the social sphere of the individual. The more observable the results of innovation are, the more likely it is to be adopted;
- "Complexity": is the degree to which an innovation is perceived as difficult to understand and use (Rogers, 1962). People who feel confident with the functioning of the innovation will be more likely to adopt it rapidly, while individuals who have difficulties in using the new product will be more reluctant.

The DOI Theory has been widely studied by many scholars and adopted as reference model in further research. On the basis of the factors described by Rogers, two further constructs have been elaborated by Moore and Benbasat (1991):

- “Image”: is the degree to which use of an innovation is perceived to enhance one's image or status in one's social system (Moore and Benbasat, 1991, p.195). The importance of the social sphere in the process of Innovation diffusion was considered by Roger too: in fact, he claimed that one of the most important individual motivations in adopting an innovation is the desire to acquire a social status (Rogers, 1983, p. 215). According to this concept, Rogers decided to integrate Image in the Relative Advantage category. Since several further studies (Holloway, 1977; Tornatzky, 1982 and so on) have demonstrated the different effects of the two categories in the decision to adopt an innovation, it is appropriate to consider social approval as a separate factor;
- “Voluntariness of use”: is the degree to which use of the innovation is perceived as being voluntary, or of free will (Moore and Benbasat, 1991, p.195). This category considers the individual's freedom to decide personally whether to adopt or reject an innovation. The authors demonstrated that it is more than a binary variable, as it is strongly related to the level of hierarchy of the work performed, which makes innovation either mandatory or voluntary.

Moreover, Moore and Benbasat (1991) analysed the Observability construct - the degree to which an innovation result is both visible and communicable (Rogers, 1991) - and found that if consumers' adoption depended solely on the visibility of the results, it could not be explained why software innovations (less visible innovations but still leading to a visible result) have a lower adoption rate than hardware innovations. It seems that the more concrete, tangible and visible an innovation is, the more the potential adopter creates a positive attitude towards it. In light of these considerations, the authors considered it necessary to split the Observability construct into two distinct dimensions: on the one hand the "Results Demonstrability" which includes the Observability and Communicability of the results of the innovation utilisation, i.e. their tangibility and measurability. Zaltman et al. (1993) argued that the more demonstrable an innovation is, the more visible its benefits are to the consumer and the more likely it will be adopted. On the other hand, the concept of "Visibility", i.e. the degree to which it is possible to observe someone else using the innovation.

Park et al. (2007) investigated the validity of the DOI model hypothesis by analysing the motivations of doctors and nurses in the decision to adopt smartphones. The authors assessed the relevance of Compatibility, Observability and Trialability on users' attitude to use smart devices. They also investigated the impact over users' attitude of personal (such as education, age, experience and personal traits), organisational (top management support, size, user involvement, product champion) and environmental (competitive pressure, customer satisfaction and marketing approach) factors. Park et al. (2007) found a low relevance of Trialability and individual features over the attitude of using smart objects, as also demonstrated by He et al. (2006), who in their study showed a low impact of Trialability on technology adoption. In fact, the same authors found that perceived Compatibility is the only variable influencing the adoption of Chinese companies of online e-payment. The role of Trialability was further clarified by Johnson et al. (2018), who found a positive impact of this factor over the Perceived Security of mobile payments. This result is in line with the conception of the adoption of technology intended as "learning experience": the more individuals have the possibility of testing a determinate innovation, the more they learn the functionalities and features of that very technology, increasing their confidence, perceived security and, consequently, the possibility of adopting it (Arvidsson, 2014).

Furthermore, Park et al. (2007) found a strong impact of Observability and organisational attributes. These results confirm what Rogers assumed about the importance of Observability of a product in the adoption decision: the more the use of a technological product is visible to users, the more their attitude to adopt it will be positive.

Johnson et al. (2018) have used DOI as a theoretical framework in order to investigate which factors influence m-payment service adoption. While some barriers to the use of these services are purely structural (e.g. the complex infrastructure of the payment system, the high number of stakeholders present and the existence of traditional payment alternatives with which users are more familiar), the authors focused their research on an attitudinal barrier that included Security and Privacy concerns. For this reason, the conceptual DOI model has been extended by analysing how Ease of Use (Kim et al., 2010; Shin, 2010a, 2010b), Relative Advantage (Rogers, 1962), Visibility (Rogers, 1962), and Perceived Security predict the usage intention of mobile payments. Moreover, they have studied how perceived privacy risks, ubiquity and trialability affect indirectly usage intention, being mediated by perceived security. Johnson et. al (2018) findings demonstrate the positivity of all the analysed factors except for perceived privacy risks, which have a negative impact on perceived security. Their results have provided important contributions to previous literature, by giving relevance both to perceived privacy risks and security issues, and by analysing their impact on individual willingness to adopt innovative products under the Theory of Diffusion lens.

Analysing the DOI theory, Moore and Benbasat (1991) focused on the difference between primary and secondary attributes: the former are the real and objective intrinsic characteristics of an innovation, regardless of the perception that the individual may have; the latter instead indicate the perception that the potential adopter has of the attribute. For instance, the price is an objective numerical value at which a product is sold on the market: this can be perceived as expensive by a consumer and as cheap by another, in relation to various factors such as individual economic availability, and so on. The fact that the same primary attribute can be perceived differently by each individual, leads the authors to emphasise the importance of considering the "perceptions of attributes" as essential to the analysis. "*The behaviour of individuals, however, is predicated by how they perceive these primary attributes*" (Moore and Benbasat, 1991). Going even deeper, the authors argued that the key variable for the analysis of Innovation diffusion is the consumer's "perception *of using* the innovation", rather than the "perception *of the innovation* itself".

2.1.2 Theory of Reasoned Action and Theory of Planned Behaviour

In 1975, Fishbein and Ajzen have developed the Theory of Reasoned Action (TRA) on the basis of which Ajzen will elaborate the Theory of Planned Behaviour in 1991.

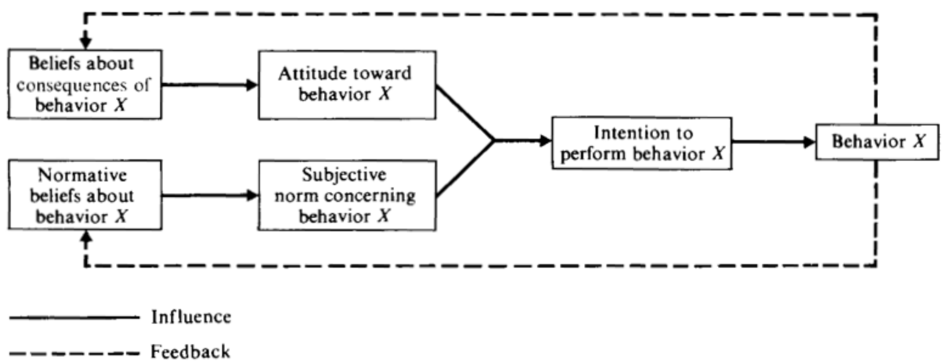
Proceeding in order, Theory of Reasoned Action is a model that predicts human behaviour by underlining for the first time the centrality of the individual through the cognitive process. The basic assumption is that human beings engage in behaviour that directly derives from information and beliefs formed over time on that particular behaviour. Therefore, TRA analysis takes into account two important aspects: on the one side, the socio-cultural diversity and the influence of the external environment on individuals are introduced; on the other side, individuals' different mindsets and backgrounds are considered, which lead them to elaborate the same information differently, and develop distinct beliefs about the same topic.

According to the model, the direct determinant of human behaviour is the "Intention" to perform: it is the degree to which individuals are likely to plan to act, spend resources and make efforts with the purpose of achieving a specific behaviour.

Furthermore, the intention to behave is directly determined by the formed beliefs about the behaviour in question. The two belief-based constructs of the model are:

1. "Attitude toward behaviour": it concerns the evaluation of the consequences (favourable or not) which the behaviour performance leads to. It measures the degree by which the individual would or would not engage in the behaviour in first person;
2. "Subjective norm": it concerns the opinion that people important to the individual have regarding that behaviour. More deeply, it is the individual perception that his/her social reference group approve or not approve the performance of the behaviour or would perform it personally.

Figure 1



Source: Fishbein, M., & Ajzen, I. (1975). "Belief, Attitude, Intention, and Behavior: An Introduction to Theory and Research Reading"

As general rule of the model, the more attitude towards behaviour and subjective norms are strong and positive, the more the individual will be motivated to implement the behaviour. The determinants of intention can assume different weights depending on the person in question, the behaviour to be evaluated and the environmental conditions. The intention to engage in a particular behaviour therefore derives from a particular combination of attitudinal and regulatory factors.

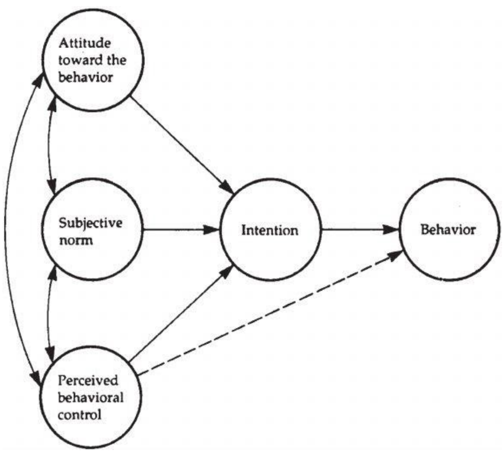
Several studies have adopted TRA theoretical framework for the analysis of the innovation adoption process: the resultant basic assumption is that the attributes of innovative products are of particular importance in the process of creating the intention, thus creating a positive (or negative) attitude towards innovation, leading to the decision of adoption (or rejection). Touzani et al. (2018) in their research about motivations behind connectedness using the IoT, have identified three main attributes that consumers desire from an IoT product: "Perceived Ease of Use", which is the degree by which the individual thinks that using the product/service will be easy and free of extra effort; "Perceived Ubiquity", which indicates the ability to use the product/service anytime and anywhere; "Time Saving", which refers to the device's ability to help consumers to save time in various decision-making processes. Time and energy are two factors that people usually try to minimize, and smart objects are intended as means to achieve this goal. The authors have demonstrated the positive impact of these three factors on the perceived value of the innovative product, and therefore on its adoption. Furthermore, confirming the relevance of individuals' personal and social traits, the study noted the importance of four psychological traits: "Technophilia" (taking from the concept of "Innovators" introduced by Rogers, which refers to people with an innate attraction to technology and innovation), "Innovativeness" (the individual's propensity to adopt technological innovation), "Anxiety" (mental state of apprehension and fear probably related to a lack of personal ability in using technology), and "Skepticism" (tendency not to believe in a particular product, feeling of apprehension for the harmful consequences of technology). According to the study, the first two have a positive impact on the adoption of products with IoT technology, while the last two have a negative influence.

Despite Touzani et al. (2018) findings, many other studies have been conducted in various situational fields (e.g. in large organisations, institutions, smaller groups, and so on) to verify the impact of general attitudes and personality traits on human behaviour. Given that these studies' results have demonstrated that attitudes and personality traits are not significant drivers of behaviour, scholars have stopped considering the latter as direct predictive factors for behaviour of adoption and rejection (Wicker, 1969). In order to overcome these findings and understand the role of individual personality traits and attitudes towards human behaviour, the "Principle of Aggregation" of specific behaviours across occasions, situations, and forms of action was developed (Epstein, 1983; Fishbein & Ajzen, 1975). The idea behind this principle is that each individual behaviour is determined not only by general dispositions, but by a myriad of other situational factors that contribute to generate it. The peculiarity of each observed situation and the need to analyse its own characteristics are therefore underlined. In this way, the scholars' aim was to demonstrate that attitudes and personality traits are implicit in human behaviour, but that their influence in specific situations is significantly attenuated by other situational factors, and therefore difficult to perceive and measure. Consequently, these two drivers impact merely in an indirect way on the final behaviour of adopting or rejecting an Innovation, influencing other factors that are more straightforwardly related to the specific behaviour under analysis.

Since TRA considers intention as a good predictor of behaviour only in cases in which individuals have full control over their behavioural performance, the Theory of Planned Behaviour (TPB) has been developed

(Ajzen, 1991). Defined as an extension of the Theory of Reasoned Action, TPB maintained the central focus on the intention of implementing a certain behaviour, which incorporates individuals' motivational facts (such as how much they want to perform that behaviour, how much effort they intend to put into it, and so on). Similarly, the general rule is that the stronger the intention, the more likely the behaviour will be performed. It is assumed that the intention to perform a behaviour is manifested through a real action only if individuals want to (i.e. if there is a volitional control). So far, we are still in the individuals' motivational sphere. Although many behaviours fall within the motivational sphere, many others require the presence of non-motivational factors and opportunities (such as the availability of money, time, energy or people). The set of such factors represents what is called the "Actual Control" of individuals over behaviour. According to this, the TPB argues that a certain behaviour will be successfully performed by individuals who intend to execute it (motivational sphere) and who have the necessary resources to do so (ability). However, what makes the Theory of Planned Behaviour different from the TRA is the concept of "Perceived Behavioural Control", which indicates people's perception of the degree of easiness or difficulty in performing a behaviour. According to Ajzen (1991), Perceived Behavioural Control has a twofold impact on behaviour: on the one hand, it has an indirect influence being mediated by intentions; on the other hand, it has a direct impact on behaviour. In other words, human behaviour is directly determined by both intentions and perceived behavioural control, as shown in the Figure 2.

Figure 2



Ajzen's Theory of Planned Behavior. Source: Ajzen (1988, p. 133).

According to the author, considering an equal intention of behaviour, a greater perceived behavioural control increases the individual's effort to successfully perform the behaviour in question. Namely, considering the same intention of two individuals who want to learn how to ski, the one who feels more self-conscious about equipment and sport in general will be more likely to succeed in the desired intention than the other one. The construct of "Perceived Behavioral Control" (Ajzen, 1991) was applied by Compeau and Higgins (1995) to the context of technology utilization, leading to the elaboration of the concept of "Self-Efficacy": this term indicates the judgement individuals have about their ability to use a technology in order to complete a job or a task. “Self-efficacy” therefore plays a fundamental role, and through the years numerous studies have confirmed the importance of confidence in personal abilities for the successful performance of a certain behaviour (Bandura, 1982). Self-efficacy does not concern with the skills one has, but with judgments of what one can do with whatever skills one possesses (Bandura, 1986, p. 391). It is important to consider this driver in the analysis of consumer behaviour towards Innovation. In this regard, many studies have demonstrated the positive relationship between Self-efficacy and the intention to adopt a certain technology: people who feel confident about their ability to understand the use of smart products, tend to show less oppositional reactions (Z. Mani et al., 2018). In the specific field of technology, Park et al. (2007) demonstrated that Self-efficacy has a significant positive influence on Perceived Ease of Use and Intention to use a smartphone. On the same line are the findings of Compeau et al. (1995), which claim that Self-efficacy has a key role in the formation of individual feelings and behaviours: the authors found a positive correlation between this driver and computer use.

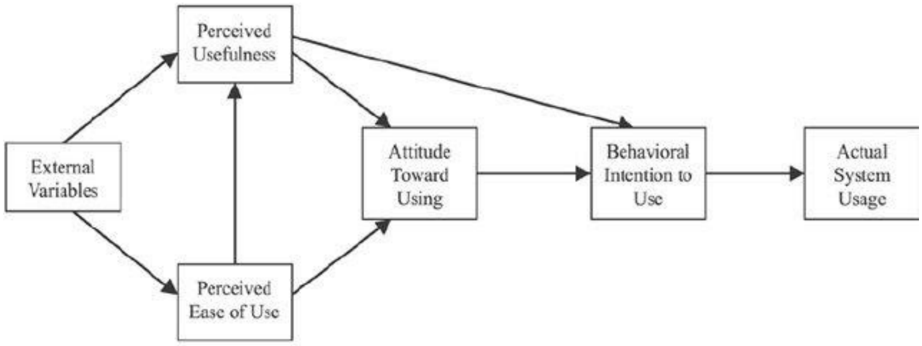
To conclude, the Theory of Reasoned Action and the Theory of Planned Behaviour are two fundamental models which have radically contributed to the understanding of the cognitive process that drives human beings to implement a specific behaviour. For the purposes of my study it was important to analyse these two theories because the process of adoption of an Innovation (specifically a smart object) includes both the attitudinal and the social sphere of the individual and the Self-efficacy concept.

2.1.3 Technology Acceptance Model

In 1989, D. Davis adapted the Theory of Reasoned Action to a microsocial system, examining the individual’s intention to use a computer. The Theory of Acceptance Model (TAM) is relevant to my research, since it has revisited a strictly behavioural model (TRA) by considering the specific technological sector, which is the focus of my study.

Davis has removed the attitudinal variable from the model in order to better focus on the “intention” to accept and use a technology. The basic assumption of TAM is therefore that the individual adoption system is influenced by two main variables: “Perceived Usefulness” (PU) and “Perceived Ease of Use” (PEOU). The former consists in the belief that the use of the innovative product improves individual’s work performance; the latter concerns the fact that the use of the product is easy and effortless. Davis (1989) has also analysed the relationship between these two constructs and concluded that the more a product is perceived by the user as easy to use, the more it will be perceived as useful in the work context. In light of the DOI model discussed above, it is evident the strong similarity with Rogers' constructs (in particular: PU and Relative Advantage; PEOU and Complexity).

Figure 3



Source: Davis et al. (1989, p. 985)

The model shows that the external variables directly affect the "Perceived Ease of Use" and the "Perceived Usefulness"; the PU is considered both as a dependent variable (as it is predicted by the PEOU) and independent (as it directly impacts the attitude towards using and the Behavioural Intention to use). Many studies have been conducted using the TAM framework and analysing the relationships between the main variables introduced by Davis. In particular, Lee et al. (2003) reviewed TAM history, analysing differences and similarities compared to TRA, and understanding the relationship between the variables considered in the model. From the analysis of a total of 101 studies, Lee et al. (2003) have obtained interesting results about the relationship between the main drivers of TAM: 74 studies found the relationship between Perceived Usefulness and Behavioural Intention to be highly significant. On the one hand, this finding demonstrates the above-mentioned cruciality of functional attributes in the formation of the intention: users will be more inclined to adopt a certain product, the more they perceive it to be useful for their performance. On the other hand, Perceived Ease of Use has been detected as a significant variable for Behavioural Intention only by 58 studies. This result confirms the concerns raised by several scholars (Gefen and Straub, 2000; Keil et al., 1995) about the importance of the variable Perceived Ease of Usefulness, who underlined the relevance of Perceived Usefulness noting that "*no amount of PEOU will compensate for low Usefulness*". However, the relationship between PEOU and PU is revealed by 69 studies and therefore highly significant.

The effectiveness of TAM has been mostly demonstrated in studies in professional settings. Park et al. (2007) used TAM as a framework to investigate the motivations of doctors and nurses to adopt a smartphone. The results of their research confirmed the validity of the model especially in the professional field, as they found that the intention to adopt a smartphone is influenced primarily by individual attitude, followed by Perceived Usefulness and Self-efficacy. In agreement with previous studies, the authors found that the PU and PEOU are both positive determinants of attitude, even though in different ways: the former has a greater impact than the latter, confirming what has already been affirmed by the previous scholars (Lee et al., 2003; Gefen and Straub, 2000; Keil et al., 1995), so that the Perceived Usefulness of the product plays a more influential role than the Perceived Ease of Use of the same. Park et al. (2007) findings further emphasised the importance of self-efficacy, confirming that the more confident individuals feel with a given technology, the higher the Perception of Ease of Use will be (as already discussed in the TPB section).

Mani et al. (2016) demonstrate the importance of Perceived Usefulness, as a factor with a significant negative effect on consumer resistance to smart products.
Moreover, Touzani et al. (2018) identify utilitarian value as one of the three fundamental aspects of users' perceived value: in accordance with their study, users are looking for utility in smart objects the smart device becomes the means that, through its functional features, enables them to achieve the desired goal.
Based on TAM empirical results, Davis elaborates TAM1 adding two further theoretical constructs to the model in order to give more weight to sociological variables. The first construct is related to social influence and includes the concept of Subjective Norms: in general, the effect of subjective norms is stronger if individuals believe that by following them their reputation within the group will improve. These include the drivers of "Voluntariness" and of "Image" with respect to the group (already described in paragraph 2.1.1). Finally, the second construct includes instrumental cognitive processes that directly impact Perceived Utility: these include "Relevance to work", "Quality of performance" and "Demonstrability of the result".

2.1.4 User Acceptance of Information Technology (UTAUT and UTAUT2)

Venkatesh et al. (2003) developed the User Acceptance of Information Technology (UTAUT) theory, with the aim of systematising the existing models and theoretical contributions in the field of technology acceptance so far. The topic of the adoption of an innovation has been extensively discussed by various authors (as we have seen in the previous paragraphs), and this has always led new researchers to compare the available models and to choose the "best" one to use in their study, renouncing the possible contributions of the excluded alternative models. In order to integrate the fragmented theoretical framework on the adoption of technology, Venkatesh and his colleagues provided a general literature overview, comparing user acceptance models and analysing their similarities and differences. The ultimate goal of the authors is actually to develop a unified theory of user acceptance of technology based on the key points of the previous theories and on their similarities.
The UTUAT is a model developed in an organisational setting, with the goal of explore employees' technology acceptance and use.
The analysis therefore included models that consider the use of technology as a dependent variable, and intention as the predictive variable of behaviour. Specifically, these are eight: Theory of Reasoned Action (TRA), Technology Acceptance Model (TAM), Motivational Model (MM), Theory of Planned Behaviour (TPB), Model of PC Utilization (MPCU), Diffusion of Innovation (DOI), Social Cognitive Theory (SCT), Combined TAM and TPB (C-TAM-TPB). After discussing, analysing and comparing the variables involved in the models listed above, Venkatesh et al. (2003) empirically validated the results and obtained a strong support for the elaboration of the UTUAT. In particular, the authors found three determinants directed to the "Intention" to use technology ("Performance Expectancy", "Effort Expectancy", and "Social Influence"), and two determinants directed to "Usage behaviour" ("Intention" and "Facilitating Conditions"), as described below:

- "Performance Expectancy": this variable is contained in the Social Cognitive Theory (SCT) and refers to the performance consequences of using a technology, i.e. the performance expectations that deal with job-related outcomes (Compeau and Higgins, 1995). Performance Expectancy (PE) is the most predictive factor of Intention, which is significant both in settings of compulsory and voluntary adoption of technology. The correlation between PE and Intention is attenuated by demographic factors (gender and age): in particular, Intention to adopt an innovation is stronger in men and young workers. These differences are supported by researches in demographic field which on the one hand suggests that men are more task-oriented than women, on the other that young workers give more importance on extrinsic rewards. Therefore, Gender and Age are two moderators of Performance Expectancy on Intention.
  The specific drivers impacting Performance Expectancy are Perceived Usefulness (TAM/TAM2 and C-TAM-TPB), Extrinsic Motivation (MM), Job-fit (MPCU), Relative Advantage (IDT), and Outcome Expectations (SCT).
- "Effort Expectancy": is the degree of ease perceived by individuals in using a specific technology. Effort Expectancy (EE) has been found to be extremely significant in both voluntary and mandatory settings of technology adoption. Instead, its intensity decreases through the adoption phases: individuals perceive a greater effort in the first step of adoption which decreases in subsequent periods, as they become more familiar and practical with the system. The variables that impact on EE are: Perceived Ease of Use (TAM/TAM2), Complexity (MPCU), and Ease of Use (DOI).
  Again, demographic variables are moderating the relationship between EE and Intention: as far as Gender is concerned, women perceive more EE than men; with regard to Age, more mature workers perceive a greater complexity in understanding and using certain innovative technological systems. Finally, Effort Expectancy will be a strong determinant of the Intention for women and older workers, especially in the early stages of adopting a new system.
- "Social Influence": is the degree to which individuals perceive the opinion of relevant people about whether or not to adopt innovation. This construct has been widely used in the previous literature (TRA, TAM, TPB, C-TAM-TPB, MPCU) referring directly or indirectly to the fact that the individuals' adoption behaviour is strongly influenced by the way their reference group considers the use of the technology in question. However, the authors found four moderators of Social Influence: the first is Voluntariness, as Social Influence has resulted significant in mandatory adoption settings and not in voluntary ones; the second is Gender, as women seem more sensitive to the opinions of other people, and therefore perceive more the influence of the reference social group; the third is Age, as more mature individuals perceive a greater social influence than younger ones; the fourth is Experience, as Social Influence decreases with the increasing of individual experience with the new system.
  Social Influence (SS) is determined by: Subjective Norm (TRA, TAM2, TPB/DTPB and C-TAM-TPB), Social Factors (MPCU), and Image (DOI).
- "Facilitating Conditions": it is the degree to which individuals believe that exist an organizational and technical infrastructure in order to support the use of the innovative system. This is a direct determinant

of Usage Behaviour and has been detected to be significant when examined in conjunction with Age and individual Experience moderators: specifically, the authors found that only the more mature and more experienced employees are affected by "Facilitating Conditions".

- “Intentions”: as extensively discussed in the literature, the authors also demonstrate the direct significance of the Intention on Usage Behaviour.

With the aim of extending the UTAT model from the organizational context to the specific consumer setting, UTAT2 (Venkatesh et al., 2012) has been developed: the four constructs that influence the use of technology in accordance with UTAT (i.e., Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions) have been adapted by the authors to the context of individual consumers in order to predict their behavioural intention to use a technology.
Moreover, UTAT2 incorporates three new constructs:

- “Hedonic motivation”: it is defined as “*the fun or pleasure derived from using a technology*” (Venkatesh et al., 2012). It is the enjoyment perceived by individuals while adopting a technology. Findings show that Hedonic Motivation (HM) is a factor that significantly impacts the individual consumer's Intention to use a technology, even more than Performance Expectancy (in non-organisational settings). In addition, three HM moderators were identified: HM has a greater impact on young (Age) men (Gender) with little technological experience (Experience). The study showed that both utilitarian (functional features of the product) and hedonic (fun-related features) benefits are important drivers of using technology for the consumer.
- “Price”: this variable deals with the individual perceived price of a technological product. Perceived Price is defined as “*consumers’ cognitive trade-off between the perceived benefits of the applications and the monetary cost for using them*” (Dodds et al. 1991). Consequently, Price affects Intention positively when benefits derived from using the innovation are perceived as greater than the monetary cost. This construct is particularly important because individual consumers perceive the Price as a personal sacrifice compared to the employees of an organisation, who usually do not sustain that cost directly. In this regard, it is necessary to consider the mechanisms of economic constraint and personal monetary availability as determinants of individual Price Perception. Such economic sacrifice can be a decisive factor for individuals in deciding whether or not to adopt an innovation. The introduction of the price variable completes the UTUAT model, which considered only the effort and time factor. The analysis found that demographic characteristics of Gender and Age are important mediators between Perceived Price and Intention: in particular, it was found that mature women perceive the price variable more strongly than other consumers.
- “Experience and Habits”: the former refers to the opportunity to use a certain technology and is measured by the time passed since the first use of the technology; the latter concerns the extent to which people tend to perform behaviours automatically because of learning (Limayem et al. 2007). Experience is a necessary but not sufficient condition for habits to be developed: in fact, in the same period of time

different levels of habit can be reached depending on the intensity of technology use and familiarity reached. For this reason, the authors consider habits as the result of the experience previously made. Findings have shown that habits have both a direct and indirect effect on Intention.

2.1.5 Criticisms and Limitations

Despite being widely used as a lens for many studies and researches on the diffusion field, the previously described models have been considerably criticised.

One of the heavier criticisms is the fact that they analyse only reasons for adoption, without considering the reasons against adoption. Several studies have examined the importance of Innovation, proving that is one of the major drivers in a wide range of sectors. For example, BCG conducted a research in 2019 which shows that innovative companies create more value compared to traditional businesses: on average they generate an annual total shareholder returns of 3.6 percentage points higher than those of their competitors ("Overcoming the Four Big Barriers to Innovation Success", 2019). Contrary to evidences which demonstrate the economic potential of innovations, data shows that innovations still tend to fail: according to Clayton Christensen 95% of innovative products fail (Nobel, 2011), which correspond to an average of 19 out of 20; moreover, Startup Genome Report claims that 92% of startups fail, with an average of 11 out of 12 (Techli, 2012). Moreover, across different product categories 40-90% of innovations never become a commercial success (Gourville, 2006). There is a clear contradiction between the above-mentioned numbers and the innovation potentials, which requires for studies to be conducted in order to identify the reasons why there is still strong resistance to those products.

For a considerable amount of time, scholars who implemented the literature on adoption have been focusing on reasons for performing a certain behaviour rather than not performing it, assuming that the reasons for the latter were basically the exact opposites of the former. Sutton (2004) defined this phenomenon as "Complementary Assumption", stating that it may be acceptable in the case of measures of global intentions or attitudes, but not in the case of measures of underlying cognitions (such as reasons). A practical example is the one that follows: on the one hand, we consider the "adopters" as people who decide to use homeopathic products being contrary to traditional medicines; on the other hand, "rejectors" are those who use pharmacological medicines. The adopters of homeopathic medicines may be driven by many different reasons, such as traditional medicines damage to human health, the possible long-term dependence of pharmaceutical drugs and so forth. On the other hand, if we ask to rejectors why they do not use homeopathic products, the answer will not probably be "because they are harmful to my health in the long term" or "to become addicted to them" (i.e. the exact opposite of the adopters), but it will be a different one (such as the rapid effectiveness of pharmaceutical drugs or others). Moreover, if some people decide to use public transport to get around the city for environmental reasons and to avoid creating pollution, it is not obvious that people who use private transport do so with the precise objective of causing pollution and damage to the environment. There will be other motivational factors which are not logically opposed, and which need to be analysed. The reasons against a certain behaviour will therefore include further considerations, representing a different category from the reasons *pro.* Hence, it is clear from these examples that the reasons in favour and the reasons against adopting a certain innovation are not necessarily speculative and corresponding and should be considered as separate categories. Many authors have emphasised the different role of innovation rejection compared to the adoption one: according to Gatignon et al. (1989), the rejection of an innovation is not explained by the same drivers that explain adoption, since "*Innovation resistance is not the obverse of innovation adoption*" (Ram, 1987). Therefore, it is important not to limit the analysis to the factors that positively influence the adoption, and to extend it also to negative drivers leading consumers to rejection. Hence, it is necessary to consider the non-logical correspondence between factors for and against the adoption of an innovation. Claudy et al. (2014) adopted the Behavioural Reasoning Theory (Westaby, 2005) as a conceptual framework to analyse the cognitive decision-making process of adopting an innovation. This model categorically distinguishes the reasons for and against the adoption of an innovation, considering their qualitative differences and their distinct influence in the decision-making process of individuals. In fact, the BRT model assumes that reasons predict attitudes "*because they help individuals justify and defend their actions, which promotes and protects their self-worth*" (Westaby, 2005, p. 98). Claudy et al. (2014) stress the crucial role of reasons for and against adoption in shaping individuals' positive or negative attitudes towards Innovation. Additionally, being reasons context-specific constructs that justify individuals' actions, they differ from beliefs, which are *a priori* assumptions that may or may not be related to the adoption of the behaviour. Therefore, beliefs are not always hidden determinants of the adoption decision, but it is necessary to consider the contextual factors - such as the type of innovation in question or the context of adoption - that influence the reasons for adopting or rejecting an innovation. Thus, the decision to adopt an innovation derives from the intention to adopt it, which is directly influenced both by the reasons -for and against- and by the attitude towards adoption, which in turn is directly affected by the reasons for and against and by individuals' values. Values are defined as motivational constructs that refer to goals that individuals aim to achieve (Schwartz, 2006). These, in addition to the reasons for and against, also affect the attitude towards adoption.

In the light of these findings, my analysis will focus on the identification of reasons for and against the use of IoT technology, with particular attention to the possible relationships between these drivers, without assuming *a priori* their correspondence.

Moreover, in their study, Chatzidakis and Lee (2012) underline the difficulty of identifying and analysing the causes of anti-consumption in comparison to those of consumption. In fact, it is not complicated to measure consumption as it is manifested directly in an action (i.e. the purchase of a certain product or service). Consequently, the reasons that have led to consumption are easily identifiable. By contrast, anti-consumption is a negative action, a non-action, which therefore has no evident effects in the reality of the facts other than a non-choice to adopt a certain product or service. The conscious avoidance of a purchase constitutes a non-event (Friedman, 1985), which can only be measured indirectly in a given environment (through tools such as interviews, forums and so on). However, this reasoning seems to be appropriate for the analysis of the reasons for and against the adoption of smart objects: consumers who will form a positive attitude will be easily identifiable in a given situation, as they will have purchased the innovative product or service. This type of consumer will easily be able to answer the question “why did you buy an innovative product?”, as the adoption of the product will have been driven by concrete motivations, and the choice will have been conscious and intentional (at least in most cases). Differently, those who will have formed a negative attitude will be more difficult to identify, as they will have rejected the innovation through a non-purchase of the innovative product or service. In most cases, the non-action has hidden and often unconscious motivations, therefore for this type of consumers it will be more difficult to answer the question “why you did not buy the innovative product?”. Considering innovation as a process that has as its output certain products and services, it is assumed the validity of what has been stated by Chatzidakis and Lee (2012), who considered the anti-consumption as those reasons against consumption that are expressive and consciously articulated, that may be used as accounts, explanations or narratives of why people “go against” (Kozinets, Handelman and Lee 2010) and “express resistance to, distaste of, or even resentment or rejection” (Zavestoski 2002) of specific brands (Thompson and Arsel, 2004), behavioural and product categories (Piacentini and Banister, 2009), and/or culture altogether (Leonard-Barton, 1981; Shaw and Newholm, 2002).

In addition, the Diffusion of Innovation Theory has been widely criticised since Rogers does not consider the symbolic meaning of technology for the consumer in his analysis. The diffusion of certain technological innovations can be fully comprehended only by considering the cultural conditions of the society in question and the values of the specific historical period. For instance, when mobile telephony was introduced the “innovators” have adopted mobile phones very rapidly, and this can be understood only by considering the value of deterritorialization of the time, people’s desire to move continuously, the need for contact with their social target groups and so forth. Similarly, the adoption or rejection of IoT technology must be evaluated in the light of the socio-cultural needs of the time in which we are living.

In other words, the major limitation of the literature on adoption models is that they merely investigate the drivers that positively influence the decision of adoption, assuming that the decision of rejecting an innovation derives from their exact logic opposites. Not considering the qualitative difference between the factors pro and against adopting an innovative product, leads to an incomplete and partial framework for a comprehensive research.

In conclusion, the next table summarizes the main adoption factors examined so far and identified by the previous literature.

Reference Model	**Constructs**	**Definition**
Diffusion of Innovation (Rogers, 1962).	Relative Advantage	"The degree to which an innovation is perceived as better than the idea it supersedes" (Roger, 1962).
	Compatibility	"The degree to which an innovation is perceived as being consistent with the existing values, needs, and past experiences of potential adopters" (Moore and Benbasat, 1991).
	Trialability	"The degree to which an innovation may be experimented on a limited basis" (Rogers, 1962).
	Observability	"The degree to which the results of an innovation are visible to others" (Rogers, 1962).
	Complexity	"The degree to which an innovation is perceived as difficult to understand and use" (Rogers, 1962).
	Image	"The degree to which the use of the innovation is perceived to enhance one's image or status within a social system" (Moore and Benbasat, 1991).
	Voluntariness	"The degree to which the use of the innovation is perceived as being voluntary or of free will" (Moore and Benbasat, 1991).
	Result Demonstrability	"The tangibility of the results of using the innovation, including their Observability and Communicability" (Moore and Benbasat, 1991).
	Visibility	"The degree to which it is possible to observe someone else using the innovation" (Moore and Benbasat, 1991, p. 203).
Theory of Reasoned Actions (Fishbein and Ajzen, 1975)	Attitude Toward Behavior	"The individual positive or negative feelings about performing the target behavior" (Fishbein and Ajzen, 1975).
	Subjective Norm	"The individual perception that most people who are important to he/she think he/she should or should not perform the behavior in question" (Fishbein and Ajzen, 1975).
Theory of Planned Behavior (Ajzen, 1991)	Perceived Behavioral Control	"The perceived ease or difficulty of performing the behvior" (Ajzen, 1991)
	Self-efficacy	"Confidence in personal abilities for the successful performance of a certain behaviour" (Bandura, 1982).
Technology Acceptance Model (Davis, 1989)	Perceived Usefulness	"The degree to which a person believes that using a particular product would enhance the job's performance" (Davis,1989)
	Perceived Ease of Use	"The degree to which using a particular system would be free from effort" (Davis, 1989)
	Subjective Norm	Adapted from TRA/TPB and included in TAM2 only
User Acceptance of Information Technology (Venkatesh et al., 2003)	Performance Expectancy	"The performance-related consequences of the behavior. Specifically, performance expectations deal with job-related outcomes" (Compeau and Higgins, 1995).
	Effort Expectancy	"The degree of ease perceived by the individual in using a specific technology"
	Social Influence	"The degree to which the individual perceives the opinion of people important to him/her about whether or not to adopt innovation"
	Facilitating Conditions	"The degree to which individuals believe that extist an organizational and technical infrastructure in order to support the use of the innovative system"
UTUAT2 (Venkatesh et al., 2012)	Hedonic motivation	"The enjoyment perceived by the individual in using a technology"
	Price	"Cognitive trade-off between the perceived benefits of the applications and the monetary cost for using them" (Dodds et al. 1991).
	Experience/ Habits	"Extent to which people tend to perform behaviors automatically because of learning"

2.2 Literature on Resistance

Although over the years most of the studies have been conducted with the purpose of identifying the factors of innovation adoption, there is a less-established strand of studies that have been focused on resistance analysis, detecting the main innovation barriers for consumers (Garcia et al. 2007; Kleijnen et al. 2009; Ram 1987; Ram and Shets 1989). As mentioned in the first chapter of this study, it remains undisputed that innovation is a key driver for human development and corporate progress. The fundamental applications of IoT products in the various fields and the benefits they provide, as well as the creation of value for the different stakeholders, have been extensively analysed. Nevertheless, the failure rate of innovative products is still high, and one of the major reasons for the market failure of such products is the resistance implemented by consumers (Ram and Shets, 1989). It is necessary to give importance to the comprehension of the resistance factors in the first stage of the innovative product life cycle, since "*adoption begins only after the initial resistance offered by the consumers is overcome*" (Ram, 1987, p.208).

It is important to clarify that the "consumer resistance to innovation" refers to the process by which individuals reject an innovation after perceiving it as such, namely as something new compared to the previous situation. If individuals do not perceive novelty, the issue is not consumer resistance, but the ability of the firm to innovate or to communicate the innovation correctly (Ram, 1987). According to Ram (1987), from now on we will consider innovation resistance only if consumers perceive a product or service to be innovative.

In fact, on the one hand, innovation is defined as "receptive" when it is easily accepted by the market, as it does not require consumers to move from their comfort zone. In these cases, individuals can adopt innovation without significantly changing their habits, existing belief structures, attitudes or traditions. The "literature on adoption" has focused on this type of innovation, by analysing only the positive drivers of successful innovative products and services. On the other hand, the so-called "resistant" innovations are those "*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*" (Ram and Shets, 1989). According to this definition, there are two essential reasons for consumers to resist: the first one is the degree of change imposed by innovation that forces individuals to move from their satisfying status quo, habits and daily routine. In this case the individual must learn new skills and routines or embrace new traditions and values: this is perceived as a switching cost both economic and psychological, which contributes to create a negative attitude towards Innovation, thus forming a resistance to its adoption. Indeed, consumers tend to resist to Innovations as one of many forms of resistance to change typical of human nature (Bagozzi et al. 1991), since when the Innovation is launched consumers are subjected to a change in product price, performance and functionality. The second reason is the possibility that innovation may violate the previously formed belief structure of the individual - already extensively debated in the Theory of Reasoned Action (Fishbein et al., 1975) -.

Previous literature has shown that adoption and resistance may coexist during the life-cycle of an innovative product: considering the five phases identified by Rogers (1962) that form the innovation-decision process, it is possible that the individual during the "Confirmation Phase" decides to interrupt the use of the product despite an initial period of adoption. This phenomenon is defined as "Continuance/Discontinuance Decision" and underlines the need for marketers to understand the reasons why, after a period of adoption, consumers have changed their minds, stopping to use the product. In this regard, Hsu et al. (2016) suggest that consumers continue to use IoT services because of the direct influence of three factors: attitude, perceived benefits and concerns for information privacy (CFIP). Their findings therefore suggest to marketers to maintain a positive consumer attitude over time by conveying the usefulness of the product in order to have a continuity of adoption of the IoT service or product. Moreover, it is important to consider that resistance is simply a decision taken at a certain moment: it is not an intrinsic characteristic of the individual. Being aware of this, by understanding the drivers of rejection, marketers will be able to influence the future behaviour of consumers and lead them to adoption (Ram, 1989).

In the following paragraphs, the main theoretical frameworks belonging to resistance literature and related empirical studies in the field of IoT technology and smart objects will be taken under consideration.

First of all, the "Model of Innovation Resistance" (Ram, 1987) will be described as it resumes the factors previously identified in the literature on adoption (Rogers, 1962; Zaltman et al., 1973), re-analysing them through the lens of resistance.

Secondly, attention will be focused on Ram and Shets's model (1989), as it provides the identification of the main resistance barriers, divided by the authors into functional and psychological. The model then has been extended following the approach of relevant empirical research on smart objects, investigating further resistance barriers specific to the characteristics of IoT industry.

To conclude, Bagozzi and Lee's model (1991) will be analysed in order to provide a better understanding of the consumer decision-making process when deciding to adopt or reject an innovation.

2.2.1 A Model of Innovation Resistance (Ram, 1987)

Based on the concept of resistance as a natural reaction of human beings to changes from their status quo, Ram (1987) argues that in order to achieve the adoption of an Innovation it is primarily necessary to study, comprehend and overcome the barriers to resistance. The key point of the Model of Innovation Resistance (Ram, 1987) lies precisely in understanding the factors of consumer resistance to Innovation, in order to be able to modify the Innovation itself and enable individuals to adopt it more easily. This is what Ram (1987) defines as "Amenability to Modification", which is the ability of innovation to be modified in order to overcome rejection barriers and facilitate the adoption of the innovative product. According to the model, the cycle of modifications is repeated until the latest version of the innovative product is reached, and a final acceptance or rejection by consumers occur.

The Model of Innovation Resistance (Ram, 1987) analyses the impact on innovation resistance of three groups of factors:

- "Perceived Innovation Characteristics": the characteristics introduced by Rogers (1962) and Zaltman et al. (1973) are resumed and re-examined here.

Relative advantage in this case refers to economic gain or cost saving (both in financial and social terms): the less the Relative advantage of the innovation (the more the relative disadvantage) compared to the alternatives on the market, the more consumers will tend to resist innovation.
With the term "Compatibility", Ram (1987) does not only intend the correspondence with the pre-existing values of individuals, but also with their lifestyle. The concept of "Pervasiveness" is therefore introduced, intended as the degree to which innovation requires change or adjustment in consumers' life (Barnett, 1953). The greater is the pervasiveness (the lesser is the compatibility), the greater is the behavioural change required, and the greater is the resistance to innovation.
Risk (functional, psychological, social) is less perceived in "Minor" or "Continuous" innovations, while it is more perceived in "Major" or "Discontinuous" innovations, also increasing consumer resistance.
Trialability is linked to the concept of divisibility, defined as the possibility of attempting an innovation in phases. The less the possibility to try an innovation before buying it (and the less the divisibility), the greater the innovation resistance.
By "Communicability of Innovation", Ram (1987) refers to the ease of both the tangibility of the innovation benefits and the ability of the marketer to communicate them to consumers. The lower the communicability, the greater the resistance.
The ease of both understanding and implementing an innovation represents "Complexity". Minor complexity of the product leads to a reduced resistance to innovation.
"Reversibility" (Zaltman et al., 1973) indicates the consumers' perception that they are able to stop using the innovation if they wish to. The lower the reversibility, the greater the resistance to innovation.
"Realization" (Zaltman et al., 1973) indicates how soon the user will see the benefits of innovation after starting to use it. The less the realization, the greater the resistance.
Finally, the use of innovation can prevent consumers from continuing to use other useful innovations. The greater the inhibitory effect, the greater the resistance to innovation.

- "Consumer Characteristics": in this section, Ram (1987) analyses the psychological barriers implemented by consumers. First of all, the concept of perceived need is resumed, so that if individuals do not perceive the usefulness of innovation, they will have no valid reasons to adopt it and will be more resistant. In the same way, the more deeply established and satisfactory habits individuals have, the more they will resist changing them for an innovative product. Secondly, Ram (1987) examines individuals' personality traits, arguing that the more self-confident they are, the less they will perceive the risk of innovation and the less they will implement barriers of resistance. Likewise, the more dogmatic and anxious individuals are, the more resistant they will be to innovation. Ram (1987) also investigates the impact of attitudes and beliefs towards innovation, arguing that the more positive these are in consumers' minds, the less will be the resistance to innovation. Finally, the impact of previous experiences with innovative products is considered, assuming that the more positive these have been, the less resistant consumers will be to innovation.

- “Characteristics of Propagation Mechanisms”: the starting point of Ram’s analysis is that the characteristics of the propagation mechanisms have been extensively investigated only in cases of successful innovations, ignoring the cases in which innovations have failed. According to the author, the most effective propagation mechanisms are those that involve direct contact with consumers, as they allow a better conveyance of the product’s benefits. Moreover, Ram (1987) differentiates the innovation lifecycle in two fundamental moments: during the launch of the product on the market, the propagation mechanisms are mainly in the hands of the firm and marketers through means such as advertisement, mass media, and so on. In this case, the more effective the marketer-controlled propagation mechanisms are, the lower the resistance to innovation. Instead, when the innovation is more mature, the propagation mechanisms change and word-of-mouth, consumer reviews and so on become relevant. At this stage, the more effective the non-marketer-controlled propagation mechanisms are, the lower the resistance to innovation will be. Moreover, to reduce resistance, communication needs to be clear, convincing, credible, informative and derived from an attractive and credible source.

2.2.2 Ram and Shets’s (1989) Theoretical Framework

Ram and Shets’s (1989) model is the theoretical framework on which most empirical studies on innovation resistance are based. The major contribution of this model has been to identify two main barriers of innovation resistance: the functional and psychological ones. Many successive studies have empirically verified the validity of the model, considering the resistance to innovative products (in particular to smart objects) motivated on the one hand by the characteristics of the product and on the other hand by those of the consumer (Mani et al., 2016).

Functional Barriers

Functional barriers include resistance factors closely related to characteristics of the innovative product or service. More in detail, these refer to the use, value and risk factors of innovation.

The usage barriers are intended as “*the degree to which an innovation is perceived as requiring changes in consumers’ routines*” (Ram and Shets, 1989). In other words, they represent a situation of incompatibility of innovation with the usual habits, practices and workflows of the individual. In fact, it is important to consider that consumers - by their very nature risk-averse - tend to privilege the satisfaction status quo created over the years through beliefs and experience, especially if the innovation requires learning new skills or altering the usual routine. Therefore, well established consumption habits are difficult to overcome, as individuals tend to be attached to products that already satisfy them. Somehow, this barrier can be correlated to the one identified in TAM (Davis et al., 1989) as “Ease of use”, and which is opposed to the “Complexity” that Rogers (1962) in DOI defined as “*the degree to which people perceive an innovation as being difficult to understand and use*”. The cognitive effort necessary to adopt the innovation creates the barrier of resistance (Ram, 1989). Ram and Shets (1989) suggest a compelling product strategy to overcome the usage barrier: they argue that by integrating the innovative product with the products already employed

by consumers, innovation increases its value and consumers are more likely to adopt it. The interoperability concept of smart objects, already discussed in Chapter I, is therefore re-examined: IoT devices that work together and are connected to each other produce 40% of the total potential value that can be generated. Moreover, also from consumers' point of view, knowing that the product or service they are going to buy will enhance the functionality of a product they already own, they will be more inclined to purchase it.
The value barriers refer to the perception of the innovation price-performance ratio: it is commonly recognised among scholars that for consumers to adopt an innovation they must perceive it as having a stronger performance-to-price value than the substituted product. At this stage, it is necessary to mention the category of "Pragmatist Users", namely the consumers who perceive the cost of learning how to use the innovation as too high and not worthwhile considering the benefits it offers (Dunphy, 1995). The value barrier is correlated to what in TAM (Davis et al., 1989) is defined as "Perceived Usefulness" and that Rogers (1962) referred to in the DOI model as "Relative Advantage".
Ram and Shets (1989) argue that in order to overcome this barrier, in addition to a good product positioning and a higher performance compared to the alternatives offered on the market, it is necessary to reduce the final price by lowering production costs. As a result of this pricing strategy, consumers will perceive savings (with equal quality of performance) and will be more inclined to adopt the innovation.
The risk barriers are intended as "*the degree of uncertainty in regard to financial, functional and social consequences of using an innovation*" (Posavac et al. 2007). Since risk is one of the main features of innovation, and consumers are risk-averse by nature, it is clear that risk barriers are a significant disincentive to adoption. These barriers can be divided into: physical risks (when the product/service can damage the individual's health and physique); economic risks (the higher the price of the product/service, the higher the perceived economic risk); functional risks (risk that the product/service has not been fully tested and therefore does not function completely yet); social risks (negative assessment of the product/service by the social group of reference). Ram and Shets (1989) argue that in order to overcome this barrier, it is important to focus on its trialability: if the product or service is tested for free for a certain period of time, consumers will be able to assess its functionalities and benefits, therefore enhancing confidence and reducing the perceived risk of adopting it.

Psychological Barriers

Psychological barriers are divided into tradition and norm barriers, and image barriers.
The tradition and norm barriers refer to the concept of cultural change: these barriers occur when innovation creates a disruption in the daily routine of the individual. Therefore, the more innovation deviates from consumers' cultural traditions, the stronger the resistance to adoption. "*Attitudes can change over time, but until they do so, the barriers are up*" (Ram and Shets, 1989). The tradition barriers are related to the concept of "Compatibility" identified by Rogers (1962). Consequently, it is important to know, understand and respect the cultural traditions and social norms of the country where the innovative product is introduced in order to avoid failure.

Image barriers refer to the fact that innovative products/services acquire their own identity according to their origin, their meaning, the class to which they belong, and so forth. The more the image of the product is perceived as unfavourable, the more resistant individuals will be to adopt it. Inconsistency of images may also occur: it may happen that consumers consider their image incompatible with that of the innovative product/service (Mani et al., 2018). Ram and Shets (1989) suggest the "borrow a good image" strategy to overcome this barrier: associating innovation with a product/service that already has a positive image is a favourable way to mitigate resistance to adoption due to the image.

In conclusion, the most relevant barriers to adoption are summarised in the table below:

Resistance barriers	**Description**	**Impacting factors**
Functional barriers		
Usage barrier	The degree to which an innovation is perceived as requiring changes in consumers' routines (Ram and Shets, 1989), being inconsistent with the user past experiences, values and acceptance requirements (Lian and Ye, 2013)	- Perceived Complexity; - Negative Self-efficacy; - Conflict with existing routines and usage; - Experience/Access barriers.
Value barrier	The inconsistent perception of the innovation price-performance ratio. Lack of monetary and performance value of an Innovation (Laukkanen et al. 2008).	- Perceived (un)Usefulness; - Relative (dis)advantage; - Perceived Price.
Risk barrier (Physical, Economic, Functional, Social)	The degree of uncertainty in regard to physical, financial, functional and social consequences of using an innovation.	- Security and Privacy Issues; - Physical and health risks.
Psychological Barriers		
Tradition and norm barrier	Degree to which an innovation forces consumer to accept changes in culture and traditions (Day and Herbig, 1992)	- Desire for human contact: - Fear of technology replacing human work; - Lack of compatibility with existing offline behavior.
Image barrier	Degree to which an innovation is perceived as having an unfavorable image (Ram and Sheth, 1989).	- Unfavourable image of Innovation; - Credibility and trust of the Brand.

Limitations and Model Extensions

Even though Ram and Shets (1989) have extensively contributed to the literature on resistance, an analysis of their model in the present day leads to the identification of some objective limits.

First of all, considering the theoretical framework in the light of the technological and digital innovations of the last 30 years, the model seems anachronistic and incomplete as it does not consider essential elements of digitisation.

Secondly, the model is limited to analysing the situational antecedents of resistance - namely functional and psychological barriers - without considering the personal predispositions of the individual (Heidenreich et al., 2015; Kleijnen et al., 2009; Roux, 2007) and demographic characteristics (Laukkanen, 2016).
Due to these reasons, it is necessary to broaden the model by Ram and Shets (1989), analysing further barriers to resistance which, considering the focus of the analysis on smart objects and IoT technology and the changes introduced by digital transformation, are essential.

Smart Objects' Characteristics

It is impossible to conduct a complete analysis of the factors of adoption and resistance to IoT technology objects without considering their specific characteristics. As extensively described in chapter one, smart objects are devices equipped with sensors (through which they collect data from the surrounding environment), actuators (that activate an action and are controlled by some other entity (Mani et al., 2016), and network connectivity (which allows connection through different types of network such as Wi-Fi, RFID, Bluetooth etc.). These attributes make smart products different from traditional ones, especially for the three fundamental properties described below.
The first one is "Connectivity", which enables the device to communicate and exchange information with the surrounding environment (other devices, users, etc.). This disruptive feature is not neutral for the consumer, as the device is constantly connected and captures personal data and information, transmitting them most of the times without users' consent (Mani et al., 2016). Losing control over the amount and nature of information collected by the device (Mani et al., 2016) can be a potential source of resistance to the adoption of such products.
The second feature of smart objects is "Intelligence". The data collected thanks to the above-mentioned connectivity allow the device to take actions in total autonomy, without the help or command of human beings. The consumer thus loses control over the functionality of the product (Mani et al., 2016) and it may create a strong resistance. In this regard, Mani et al. (2018) reveal in their study that the need for human interaction is one of the main resistance barriers to IoT products and services.
The third relevant feature is "Ubiquity", which refers to the possibility to use the smart object in any place, at any time and from any device (Mani et al., 2016). It is an ubiquity of space, time and means that can cause resistance in consumers especially with regard to privacy concerns and the perception of being constantly monitored (Mani et al., 2016). Previous research has studied the role of "perceived ubiquity" on the adoption of a smart device: on the one hand, Johnson et al. (2018) demonstrated the positive influence of perceived ubiquity on the perceived security of mobile payments; on the other hand, Touzani et al. (2018) revealed perceived ubiquity as one of the attributes desired and sought after by consumers in smart objects.
One of the main consequences of the three characteristics described above is the so-called "Intrusiveness" (Mani et al., 2016). This term refers to the ability of smart devices to enter consumers' lives without permission, autonomously, capturing sensitive information and transmitting it elsewhere. In fact, the term "Big Brother Effect" indicates consumers' feeling of being constantly monitored. Intrusiveness has negative

effects on consumers, triggering negative feelings of annoyance and irritation. The key role here is covered by privacy issues. Several empirical studies have demonstrated the crucial role of privacy in consumers' evaluation of smart objects. Mani et al. (2016) found that privacy concerns have a positive effect on the perception of intrusiveness, thus amplifying consumers' resistance to adopt smart objects. In addition, Hsu et al. (2016) argue that it is important for consumers to have control over the evaluation of privacy risks and the possibility of taking action to protect their personal information. It is about having control over one's own sensitive data and the way this is collected and processed by devices: the greater the control, the lower the risk perceived by consumers (Hsu et al., 2016). This risk is identified by Mani et al. (2018) as perceived security risk, resuming the risk barriers of Ram and Shets (1989) and adapting them to the smart products field. In their study, the authors demonstrate consumers' generation of negative emotions for the loss of control over their private and personal information, adding the fear of intrusion and fraud by potentially harmful individuals or entities (this is the case of hacking, piracy and theft of financial transactions and data).

The effects of intrusiveness and privacy concerns lead to an inevitable increase in scepticism about smart products, and therefore resistance to adoption (Mani et al., 2016). The same authors two years later have analysed scepticism as an ideological and psychological barrier, which "*leads consumers to doubt the truthfulness of companies' arguments and discourses about IoT devices and promised benefits*" (Mani et al., 2018, p. 795). Hence, through their study, the authors demonstrated the crucial role of scepticism: technological vulnerability barriers (namely: technological dependence and technological anxiety) act on consumer scepticism towards IoT products, only indirectly impacting consumer resistance. The scepticism towards smart objects therefore assumes a mediating role of vulnerability to technology.

Network Externalities

Focusing the analysis on IoT products and services as "*devices which use Internet to form a huge network of smart objects*" (Hsu et al., 2016), it is necessary to enter into the merits of the so-called "network externalities". With this expression scholars intend to assert that, "*the value or effect that users obtain from a product or service will bring about more value to consumers with the increase of users, complementary products or services*" (Katz & Shapiro, 1985). In other words, previous studies have shown that network externalities directly influence the benefits perceived by consumers (Hsu et al., 2016), and therefore indirectly the intention to adopt or continue to use the smart object.

Network externalities can be of two types: the first type are the direct network externalities refer to the increase in value of IoT product/service as the number of users using it grows. In fact, Metcalfe's law states that "*a network's value is a square function of the number of its users*": the typical example is that of social networks, in which each registered user increases the value of the platform as it gives other members the opportunity to communicate with a wider network of people. Then there is the second type: the indirect network externalities, which refer to the availability of products and services complementary to the IoT product in question. Hsu et al. (2016) suggest as belonging to this category two important factors: 1)

“Perceived Compatibility”, which recalls the concept introduced by Rogers (1962), and has been found to be the most influential determinant on consumers’ perceived benefits; 2) Perceived complementarity, namely “*the availability of functions or applications serving to fill out or to complete IoT services*” (Hsu et al., 2016). Perceived complementarity is related to interoperability, a feature of smart objects by which their value increases proportionally to their ability to be connected and work with other complementary products and services.

Individual Barriers: Inertia

As not everyone adopts innovations in the same way (see Rogers’ five categories of innovation adopters mentioned in 2.1.1), not all consumers resist innovations in the same way. Inertia is the lowest level of resistance, in which individuals are simply passive and feel disinclined to adopt; active resistance is the middle level, in which consumers perceive innovation as risky and postpone the decision to adopt it (the so-called “postponers”); at the highest level stands the very active resistance, in which consumers argue the harmfulness of innovation and therefore do not simply avoid adopting it, but decide to attack it consciously (the so-called “rejectors”). The latter represents the explicit opposition, in which consumers perceive smart products as a threat and actively fight them. Being the most extreme degree of resistance, it is also the most easily identifiable and measurable, whereas the other two categories of non-users are much more hidden. Mani et al. (2018) extended the theoretical model of Ram and Shets (1989) by adding individual barriers to the traditional ones (functional and psychological). The Status Quo Bias (SQB) model (Samuelson et al. 1988) supported human beings’ predisposition to resist change due to the maintenance of a satisfactory status quo. The authors based the bias on the risk-averse nature of human beings, which lead them to perceive a novelty as generating risks and uncertainty rather than benefits. Mani et al. (2018) adopted this model and conceptualised the term inertia as the predisposition to prefer the current situation over the uncertainty of risk. In this perspective, the authors demonstrated that inertia has a double positive impact on consumers’ resistance to smart products: on the one hand, it directly impacts them, on the other hand, it is indirectly mediated by scepticism towards IoT (Mani et al., 2018).

Demographic Variables

Most scholars have conducted their researches on adoption and resistance to innovation without considering demographic variables. However, for the purposes of my research, I think it is crucial to mention the demographic differences among consumers, especially with regard to age. In particular, I consider relevant the difference in behaviour and in the approach to smart objects between young and mature consumers. The expression “mature consumers” refers to those consumers over the age of 55 (Laukkanen et al., 2007). They have great economic significance as they are growing at twice the speed of the rest of the population, and by 2050 it is estimated that one person out of five will be over 65 (Kennett et al., 1995). This phenomenon is due to the increase in life expectancy and the boom in births between 1946 and 1964 (Moschis, 2003). This

category of users deserves special attention as, in addition to representing a large part of the population, they typically also have more available money than the younger generation.
Moreover, while younger consumers were born and grown up using technology, more mature users had a completely different approach to technology: they passed from not having mobile phones, computers and the Internet, to the world of IoT, where all objects are connected to the network and where progress is fast and within everyone's reach. The approach to technology by mature consumers varies from person to person: some have accepted it immediately by learning how to use it and by becoming technology-friendly, whereas others have had more difficulty in conceiving this change. It can therefore be argued that mature consumers have become familiar with basic technology such as computers, mobile phones and the Internet. Leventhal (1997) suggests that the difference in behaviour between the two generations is due to factors driving that very behaviour: while younger people try new products for fashion or for social values, older people are indifferent to trends, and try innovations only if moved by the need to satisfy a specific personal need. Consequently, if the innovative product meets that specific need, they are inclined to try it. Hsu et al. (2016) also highlight the influence of perceived benefits in the use of IoT services: if users do not perceive the real benefit of the device, they will be less inclined to continue using it. Accordingly, it is important for marketers and companies to be clear about the functions and benefits of smart products, and above all about what needs they meet.
From their study among mature consumers, Laukkanen et al. (2007) found that on the one hand Usage and Value barriers are equally perceived by young and mature consumers; on the other hand, mature consumers are more sensitive to risk and psychological barriers – namely, tradition and image barriers –.

2.2.3 Consumer Resistance to, and Acceptance of, Innovation (Bagozzi and Lee, 1991)

"Consumer resistance to, and acceptance of, innovation" (Bagozzi et al., 1991) is a model in which consumers' decision-making process is analysed in the particular circumstances in which they have to choose whether or not to adopt an innovation, in relation to their individual well-being.
The consumer adoption/resistance process is divided into two distinct phases:

1. "Goal setting": the first phase includes the whole process by which individuals create an opinion about the innovation in question, culminating in the decision to adopt or reject.
   Individuals start to perceive a change in their usual situation, being exposed to innovation by an external factor (communication, advertising, word-of-mouth and so on) or by the recognition of an internal problem or need. This exposure leads people to an initial resistance (active in the case of actions such as boycotting, protesting or rejecting; passive when it is a consequence of well-established habits) or openness to innovation. If individuals are open to innovation, the product evaluation phase begins: the attributes, usefulness and benefits of the innovation will be examined, as well as the possible consequences of its adoption. The result of the evaluation will be the perception of innovation as an opportunity or threat. At this stage, there might be isolated cases in which, on the one hand, consumers who have perceived an opportunity may quickly reach the decision to adopt the innovation (e.g. through

impulsive buying of the product); on the other hand, consumers who have perceived a threat may immediately decide not to adopt it. However, in the majority of cases, perceptions play an important role in the decision-making process, as they elicit in the individual the so-called "anticipatory emotions", which enable an anticipated emotional assessment of the adoption of the innovation. The perception of an opportunity will therefore lead consumers to feel positive emotions (joy, pride, hope, love), while the perception of a threat will lead to negative emotions (frustration, anger, fear, sadness, anxiety, disgust, guilt, shame, and so forth). Emotions, in conjunction with other cognitive processes (namely self-efficacy, outcome expectancy and attribution process), are integrated and lead individuals to the final decision of adoption or resistance to innovation;

2. "Goal striving": at this stage individuals decide how to implement the decision taken in the previous phase. First, it is necessary to choose the means by which striving the goal; after the choice of the means, it is essential to establish the so-called "action planning", which means to decide when, where, how, and how long to act (Gollwitzer, 1996). Thus, the established plan will be carried out through concrete actions that will implement the intentions. Individuals' behaviour will be goal-oriented and will be monitored by activities of self-control of the progress of the established plan. At this stage, individuals have completed the decision-making process by implementing the choice to adopt the innovation made in the goal setting phase.

Bagozzi et al. (1991) model also emphasises the relevance of individual goals, since they motivate consumers to plan and undertake actions with the precise purpose of achieving them. The discrepancy between the objective set and the result achieved generates adoption-outcome emotions, which are positive or negative states of mind deriving from the satisfaction or non-satisfaction of a specific situation. These emotions, integrated with values, information and feedback, lead users to continue or stop the adoption of innovation. Hence, according to Bagozzi et al. (1991), the phenomenon previously described as "Continuance/Discontinuance decision" whereby consumers decide to stop using an innovative product previously adopted, derives from the negative emotions and dissatisfaction experienced after the adoption of the innovation.

The innovation of Bagozzi et al. (1991) model lies in the fact that it provides a complete framework on the decision-making process of human beings. Differently from the other models, it does not stop at the moment when individuals decide to adopt, but it also analyses the implementation of the decision, namely the concrete process by which individuals transform a decision into real action.

Furthermore, Bagozzi et al. (1991) have provided a framework for the analysis of the decision-making process by which the reasons for and against the adoption of an innovation are not necessarily the exact correspondent. In fact, while the adoption literature models used to treat the reasons against as the opposite logic of the reasons for adoption, Bagozzi et al. (1991) used the positive and negative emotions perceived by individuals as predictors of the adoption and rejection decision respectively. Considering positive and negative emotions as distinct and separate categories and not as logical opposites, it is evident that the authors also considered the unnecessary *a priori* correspondence of the reasons for and against adoption.

The following table summarizes the characteristics of smart objects and IoT technology that can act as drivers of resistance to adoption.

	Description	Drivers
Innovation Attribute		
Communicability of Innovation	The ease of both the tangibility of the innovation benefits and the ability of the marketer to communicate them to consumers.	- Observability; - Triability; - WOM;
Smart objects characteristics	- Connectivity: device ability to communicate and exchange information with the environment - Intelligence: ability to take actions in autonomy, without the help or command of human beings - Ubiquity: possibility to use the smart object in any place, at any time and from any device (Mani et al., 2016).	- Privacy and security issues; - Big brother effect; - Desire for human contact.
Network externalities	- Direct: increase in value of IoT product/service as the number of users using it grows; - Indirect: the availability of products and services complementary to the IoT product in question	- Complementary devices and Interoperability; - Perceived Compatibility; - Social value.
Consumer Attribute		
Inertia	Human' predisposition to resist change to maintain a satisfactory status quo (Samuelson et al. 1988).	- Conflict with existing routines and usage; - Indifference.
Demographics	Difference in Innovation adoption/rejection process between young and mature consumers.	- Perceived Usefulness; - Complexity.

2.3 Research Question

In the light of the economic overview discussed in Chapter I, a clear slowdown in the growth of smart device adoption by consumers has emerged, despite their potential positive benefits. As analysed in Chapter II, the previous literature focused mainly on the analysis of the positive factors that lead to the adoption of innovative products, arguing that it was not necessary to investigate the negative drivers of resistance, as the latter are the exact negative counterparts to those of adoption.

In light of these considerations, it is necessary to understand the reasons that lead consumers to create the barriers of resistance to the adoption of Artificial Intelligence objects. The aim of my research is therefore to identify the categories of adoption and resistance to smart objects by consumers, considering these two as separate clusters of factors, not assuming their a-priori correspondence and polarization. The analysis will therefore focus on the investigation of the relationship between positive and negative adoption factors, verifying whether or not there are unilateral drivers, i.e. drivers that act on adoption only positively or negatively.

Chapter III

Qualitative Analysis and Categorization of Factors Pro and Against Adoption

In this Chapter the data analysis will be carried out in order to answer the research question elaborated at the end of Chapter II.

The purpose of my research is to identify the main critical incidents affecting consumers in the process of adoption and resistance to smart objects. To do so, adoption factors and resistance barriers will be treated as separate categories which affect individuals respectively by attracting or rejecting them from a smart product. After the identification of the macro-categories, the factors affecting them positively and negatively will be analysed. Specifically, the research emphasis will be on determining whether and under which conditions the so-called "Complementary Assumption" (Sutton, 2004) is verified, i.e. the phenomenon according to which resistance factors are exactly opposite and specular those of adoption. In light of this phenomenon, many scholars have investigated only the adoption factors of smart products, consequently considering those of resistance as mere and logical opposites of the latter. Indeed, these scholars have mainly contributed to form the "literature on adoption". Some other scholars have criticized this approach, arguing that the barriers of resistance to innovations may, or may not, be the corresponding counterparts of adoption factors. On the basis of this literary debate widely discussed in Chapter II, the aim of my research is to determine whether and to what extent the factors driving the adoption of smart objects are exactly the positive correspondents of the ones for which these objects are rejected.

In order to address my research question, the analysis will be conducted following a specific procedure that consists of sequential steps as follows:

a) Identify the critical incidents of adoption and resistance that affect consumers in the smart objects' evaluation;

b) Divide them into positive and negative categories, distinct and separate, not assuming a priori their specularity or correspondence;

c) Verify possible relationship and correspondence existing among factors pro and against adoption.

In order to conduct this analysis, I have decided to examine a dataset of 61 respondents through the qualitative method, specifically using the Critical Incident Analysis (CIT) tool.

3.1 Research methodology

3.1.1 Qualitative method

The decision to use the qualitative method derives from the exploratory approach required by the research question. Specifically, the very purpose of my research is purely qualitative, since it aims to investigate the mental processes of consumers and the factors that affect the choice to adopt or reject a smart object. The qualitative method is typically implemented when it is necessary to understand certain aspects of social life, personal experiences, and perceptions of individuals in order to determine their attitudes towards a particular behaviour. Moreover, it is widely used when it is important to fully comprehend the individuals' point of view, leaving them great flexibility and freedom in responding, without limiting their answers to questionnaires and closed questions. Differently from the quantitative method, which provides data and statistics for answering questions about "how many" and "how much" on a given phenomenon already clear and unambiguous, the qualitative method aims at analysing a mostly unexplored field, answering questions such as “what”, “how” and “why”. The validity of the two methods is as unquestionable as their different approaches and objectives: hence, it is necessary to choose the appropriate methodology according to the nature and purpose of the research question to be addressed, since they are two different lenses through which to observe reality. The qualitative method is often viewed with suspicion by proponents of the quantitative approach, who frequently advance some criticism. First of all, the size of the sample examined: while quantitative results are considered more valid if a large sample is analysed - as it is considered representative of the entire population - in qualitative analyses it is not rare to base research on more limited samples. The reason is that usually the qualitative method uses a "purposive" sample, i.e. respondents are not randomly chosen, instead are carefully selected by the researcher on the basis of certain characteristics that are expected to generate relevant data to the purpose of the analysis. Typically, the aim is to create a sample with the highest variance by selecting key variables that are considered to have a decisive impact on the perspective of a given topic, thus creating a complete spectrum of opinions about the object of analysis. Moreover, in the selection of the sample, the concept of "saturation" is often used in order to indicate the condition in which the collected data tend to repeat and no longer offer new indications or directions for analysis (Charmaz, 2005). Therefore, since larger sample does not produce greater applicability, in qualitative analysis the quality of information prevails over the quantity of respondents, which is why the sample size is often small.

The second criticism advanced is the lack of rigour in qualitative analysis, and the fact that findings may be biased by the researchers' personal opinions. Some fundamental characteristics for qualitative research to be reliable are: a) Trustworthiness (the detailed description of the research process, from the literature review to the formulation of the research question, to the analysis of the data), b) Credibility (the value and internal validity of the results, i.e. how much individuals who share the same experience recognize themselves in the results obtained), c) Applicability (the external validity, i.e. the degree of transferability of the results obtained), d) Consistency (the criterion for evaluating reliability, i.e. the fact that, from the analysis of the same data, other researchers obtain the same results) (Hammarberg et al. , 2016). Therefore, qualitative

research that meets these requirements has a recognized validity and rigor of analysis on a par with other types of research.
The qualitative method is widely used for social, behavioural, managerial and sanitary research. Due to the more flexible sample selection and data collection structure, qualitative research allows a more detailed and in-depth analysis of the nature of the problem. The main reason why I chose to adopt this methodology is that it provides great freedom to the respondent to express themselves: it reveals details, opinions, points of view, experiences and perspectives and suggests new directions of analysis that would otherwise remain hidden. The qualitative method can therefore be defined as "holistic", since it does not stop at a numerical analysis of "how much" a phenomenon is relevant, but it allows researchers to respond accurately questions about "how" and "why" it happens, also considering the social, cultural, personal aspects.
Indeed, the data collected with this method are verbal and descriptive, usually collected through in-depth interviews, structured interviews or focus groups.

3.1.2 Critical Incident Technique (CIT)

The Critical Incident Technique (CIT) is a qualitative tool introduced by John Flanagan in 1954, nowadays used by researchers with the aim of capturing factual stories or episodes about a given experience (Stitt-Ghodes et al., 2000). CIT consists of a set of formalised procedures to collect observations on a specific human behaviour, with the purpose of creating a systematic respondent classification system that provides relevant insights in order to solve a practical problem. It is a classification technique based on inductive grouping procedures, belonging to the same family of quantitative methods such as factory analysis, cluster analysis and multidimensional scaling. Differently from quantitative techniques, CIT is a qualitative-exploratory approach, based on the content analysis of the experiences reported by the interviewees through "coding", which is the activity of "*discerning small elements in data that can retain meaning if lifted out of context*" (Ely et al., 1997, p.161).
Validity and reliability of CIT has been demonstrated by many scholars (Andersson et al., 1964; Ronan et al., 1974; White et al., 1981) who have proved that this technique is effective in generating a comprehensive and detailed description of a specific content domain. In the light of this, CIT is considered a valid method of analysis especially in the preliminary stages of exploratory researches (Rice et al., 1984).
Chell in 1998 has described the CIT 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 behavioral elements*" (Chell, 1998, p. 56). According to this definition, CIT analyses the responses by focusing mainly on *incidents* – observable human activities complete enough in themselves to permit the researcher to make deductions about the person performing them (Bitner et al., 1990) - that are considered *critical* from the respondent's perspective - i.e. that have actually and significantly impacted the final outcome, both positively and negatively - considering their cultural, social and personal background (Woolsey, 1986).

Usually critical incidents are collected by asking individuals (in the form of a focus groups, interviews and so on) to describe an episode about a positive (or negative) experience they had concerning the topic of analysis. For the purposes of my research, critical incidents will be intended as specific factors that lead consumers to adopt or reject the use of smart objects, deduced through the categorisation of positive and negative experiences with this type of device described by respondents.
Flanagan (1954) states that in order to correctly conduct an analysis with the Critical Incident Technique, it is necessary to proceed through five consecutive steps: a) determining the purpose of the study (in this phase it is important to choose well the words used to describe the research question, because respondents will take them as reference for reporting incidents); b) setting the plan, specification and criteria (deciding who will be the observers, the respondents, and the behaviour observed through the questions); c) collecting the data (through an interview, a focus group and so on); d) analysing the data (analysis of the thematic content of the answers through inductive reasoning); e) reporting the findings (description of the macro-categories and sub-categories identified in order to provide a complete overview of the results of the analysis).
The most challenging part of the whole process is the analysis: in this step a valid and exhaustive description of the studied behaviour has to be provided through the categorisation of the responses. Since coding is intended as the process through which data are reduced into "meaningful segments" to which names are assigned (Cresswell, 2007, p.148), the creation of categories is the main point of CIT: responses with the same meaning or motivation have to be analysed and systematically coded into categories formed by the researcher. These are identified through an inductive and necessarily subjective process, which requires "insight, experience and judgment" by the analyst (Flanagan, 1954). In order to reach the final categories, it is necessary to proceed by iteration: firstly, researchers have to read the answers to get a general framework of the situation and form the first categories. The following steps concern the investigation of the relationships among categories. Generally, there are three possible kinds of relationship (Belk et al., 2013): codes represent different elements of the same phenomenon; codes are phases, steps or elements of a process (and therefore are sequential); codes are related in an explanatory way, i.e. one code explains another. Therefore, by re-reading the dataset, when relations among the identified categories are found, these should be assembled (by creating macro-categories) and/or disaggregated (creating sub-categories) as the analysis proceeds. Every time a new code emerges, it is necessary to recode the material already analysed in order to make it unique and coherent. This "trial-and-error" procedure (Flanagan, 1954) will be carried out until the final output is reached.

3.1.3 Methodological Considerations

Since its introduction, the CIT application fields are numerous, due to the benefits that scholars have recognised both in terms of flexibility and specificity of the analysis. In particular, in the service research context, this technique of analysis has provided significant results compared to other qualitative methods. Among these, Bitneret al. (1990), through the CIT analysis of 700 critical service encounters from the consumer's point of view, have identified three types of employees behaviour that determine their

satisfaction and dissatisfaction. The relevance of Bitneret et al. findings, has initiated a series of research that continued to apply CIT in order to analyse behaviour across different industrial context (Gremler et al., 1994), from the companies' point of view (Bitneret et al., 1994) and in self-service encounters where service delivery is without employees (Meuter et al. 2000). The important results obtained thanks to CIT have contributed to research in the field of behaviour and services, inspiring many further researches (Arnould et al., 1993; Kelley et al., 1993; Keaveney, 1995; and so on), giving authoritativeness and validity to the method. Gremler (2004) provides a complete and detailed overview of the use of this approach in the field of services, summarizing its advantages and possible disadvantages.
In addition, critical incidents have been widely used in the social field for research about the learning development in various professional disciplines including education (Kuit et al., 2001), nursing (Burgum et al., 1997; Parker et al., 1995), and social work (Mills et al., 1990), in both undergraduate (Parker et al., 1995) and postgraduate (Tripp, 1993) courses, and in continuing professional education (Kuit et al., 2001; Mills et al., 1990).
With regard to marketing literature, CIT has been adopted by Badrinarayanan et al. (2008) in order to analyse the perception of marketing students in pedagogical innovations, bringing important results both in the field of marketing and innovation research.
Returning to the research objective of my study, CIT has not yet been used as a tool in the consumer behaviour field relating to innovation and technology. In particular, no research has been conducted with this technique with the aim of exploring the positive and negative critical incidents that affect consumer behaviour with respect to smart objects. With the purpose of bridging this gap, through my research I will use the Critical Incident Technique to investigate consumer purchasing behaviours in order to form macro-categories of adoption and resistance factors to smart objects, exploring the relationships that exist (or do not exist) among them, and consequently verify the validity of the "Complementary Assumption" revealed by the “literature of adoption”.
The CIT is a tool that is widely used in many fields, as it brings several analytical benefits. Gremler (2004) has systematically reviewed the marketing and management literature that has implemented CIT as tool of analysis, providing an overview of the main advantages and disadvantages of using this technique. The author has identified 141 publications based on CIT and has summarised its strengths. First, this method gives respondents complete freedom to formulate their answers: when describing their experiences, interviewees can use their own words, without depriving their accounts of force and eloquence. In this way, the research starts from the respondent's own words, since there are no preconceptions from which to begin the analysis, nor the respondent is forced into a pre-established framework. Secondly, it is an inductive method that does not require the formulation of hypotheses, suitable for the exploration of little known and scarcely documented topics. The patterns emerge during the analysis of the responses enabling the researcher to elaborate concepts and theories (Olsen et al., 1992). Third, the CIT method provides an accurate and in-depth record of the events examined (Grove et al., 1997). Fourth, the data collected through CIT analysis are highly detailed and derive directly from experience or first-hand observation and therefore

provide concrete information. Finally, CIT has been defined as a 'culturally neutral' method, as it considers the social and cultural differences of respondents. It is very effective in assessing different perceptions of the same topic based on multiple cultures (Stauss et al., 1999), mainly because it is not a priori determined what will be relevant for the analysis, as is the case in traditional surveys.

Gremler (2004) has also reported some weaknesses of CIT, which have shown some limitations of the method. First of all, it has been said that the subjectivity of the analysis can lead to a lack of reliability and validity of the model (Chell, 1998), since on the one side researchers can misinterpret the reported experience, and on the other side respondents can describe the episode in an inaccurate way (memory lapse) or re-elaborate it with regard to the reality of the facts (consistency issue). Secondly, there may be ambiguities in the interpretation of category labels and coding rules established by the researcher (Weber, 1985).

Despite the limitations mentioned, Gramler (2004) assures the validity and authoritativeness of CIT as a research technique especially in the managerial and services field.

To conclude, in order to address my research question, I consider CIT a valid and effective method for three fundamental reasons (Gremler, 2004; Sautter et al., 1995):

a) It is a goal-oriented research method, which allows me to focus on the established aim, i.e. to understand the drivers of adoption and resistance to smart objects, dividing them into macro categories, and analysing their relationship;
b) It provides a high degree of freedom both to the researcher (as it does not limit the analysis to a predefined set of variables) and to the respondents (who are not conditioned by predefined, closed questions and can freely respond by adding as many details as they want to the situations they are describing);
c) It elicits pertinent answers to real and directly experienced or observed situations by respondents.

3.2 Analysis

Data Collection

In order to gather the information needed for my research, the tool used was the open questionnaire, submitted online to respondents. This is a method of data collection generally used in qualitative research, particularly suitable for the CIT analysis that will be conducted, as respondents have ample freedom to respond and to add details that clarify their point of view and experience.

Survey

The respondents were submitted two online questionnaires in which the same questions were asked in both a negative and a positive scenario. In the first questionnaire, respondents were asked to describe a recent occasion when they had the opportunity to buy a product with built-in AI and decided *not to do* so, what are the reasons, thoughts and feelings that induced them to make this decision. In the second questionnaire, on the contrary, they were asked to describe a recent occasion when they had the opportunity to buy a product with built-in AI and decided *to do* so, what are the reasons, thoughts and feelings that encouraged them to buy it. In both scenarios respondents were asked how many and which products and services with in-built AI they already daily use, in order to have a general overview about the different use of AI products and services among consumers.

Moreover, the name of the city of origin (with which each respondent will be identified from now on) and the gender were asked, in order to have a general overview of the type of consumer (i.e. the purchase habits, the typical use of this kind of device and so on).

The decision to submit two surveys rather than just one lies in the benefits of comparing two opposite scenarios of the same person: in this way both positive and negative consumers' points of view on the same issue are analysed. The positive scenario indicates the factors of adoption, while the negative one represents the resistance drivers to smart objects: categories of adoption and resistance can be formed, and their possible relationships and correspondences can be investigated.

The Tables 1 and 2 in Appendix provide the structure of the open questionnaires submitted to respondents.

Dataset

The surveys have been submitted online to 61 respondents: it is a sample of convenience, composed of students attending university in Rome, between 22 and 24 years old. The demographic analysis reported the presence of 26 men and 35 women in the sample.

3.3 Results

3.3.1 Categories of Products and Services

The first phase of the data analysis concerned the study of the different devices and services with built-in AI that have resulted from the respondents' answers.

Firstly, it emerges that AI services are more frequently used by consumers compared to AI products: on average each respondent regularly uses 3.1 services provided with Artificial Intelligence, while possesses just 2.8 smart devices. The greater use of AI services compared to AI products is due to two main reasons: on the one hand, the intangible nature of AI services and the wide use of these algorithms by sites and companies in general, often lead individuals to use AI services without being aware of it, for instance by simply surfing the Internet; on the other hand, the main difference between product and service consumption implies that AI products to be used need consumers to consciously acquire them, while services can be used even without being purchased, sometimes even accidentally or unconsciously.

Moreover, smart products and services emerged were divided into ten different categories according to their nature and use.

From the analysis, “Voice Assistants” are the AI services most frequently discussed by respondents. Voice assistants are operators based on Artificial Intelligence, especially on machine learning algorithms, which allow to recognise human language, receive orders and perform actions thanks to the network. Smart assistants also have an internal self-learning mechanism that enables them to increasingly refine their listening and response processing. It has emerged that this characteristic leads to twofold consequences: on the one hand the sophistication of the service, which becomes more and more anthropomorphised and efficient; on the other hand it increases the perception of numerous risks related to privacy, such as the individuals' loss of control of their conversations and personal information.

The voice assistant service can be implemented directly on the smartphone (such as Siri on iPhones), or it can be purchased as a separate device (this is the case of domotic voice assistants, such as Google Home and Amazon Alexa). The Interoperability is a key feature of this service, necessary to completely exploit its full potential: Voice Assistants have to be connected to other smart objects (such as the lighting system, mobile phone and so on) in order to perform actions involving them. On the one hand, Interoperability makes consumers perceive it as a real assistant, extremely performing and multifunctional; on the other hand, it discourages the adoption by that segment of individuals who do not own other connectable devices, since they may perceive that they cannot fully exploit the Voice Assistant benefits. In the latter case, Interoperability increases the Perceived Price by individuals (they have to buy not only the voice assistant, but also the additional devices to be connected) and consequently decreases the Perceived Usefulness.

From the analysis of respondents, Amazon Alexa is the most discussed voice assistant, followed by Siri, Google Home and Google and Vodafone voice assistants.

The second category with the highest frequency is the “Streaming Online” service: these are On Demand services, both paid and free, which enable customers to view movies, videos, TV series, programs and music directly from their smartphone, thanks to the Internet connection. The Streaming Online category is composed of those respondents who have described an experience regarding Netflix, Prime Video, SkyQ and Spotify. The first two are the main online streaming platforms; SkyQ, instead, is the SKY Premium service; Spotify is a platform that provides users with an extensive music library directly on their smartphone or tablet.

Most respondents said they are satisfied with these platforms, especially because of the content personalisation service based on the individual preferences: in fact, creating a personal account is the starting point to use these platforms. The algorithm analyses the content accessed by each user on the basis of which it customises the offer, recommending possible films, TV series or music according to individual tastes. This revolutionary feature is possible thanks to AI and increases the Perceived Usefulness of the service by simplifying the search and selection of the content to see or listen.

The third category emerged is the one composed of tangible smart products, categorised as “AI products”. This category includes smartphones, computers, tablets, devices equipped with contact less technology, vehicles equipped with Artificial Intelligence, video games, beauty products and robots. It is interesting to note that interviewees frequently wanted to specify the brand of their device (computer, iPhone, iPad, air pods), highlighting the relevance of the brand in question, i.e. Apple.

Although Smart Watches are “AI products” as well, a separate category has been dedicated to them: the reason is that these belong to the Wearable segment, which are intelligent devices that people wear directly as accessories. Thanks to Artificial Intelligence, the traditional watch has become “smart” by incorporating multiple functions. Among these, being connected to the user’s smartphone via Bluetooth, it perfectly reproduces the screen of the latter allowing the reception of messages and calls directly on their wrist. In addition, another important feature is the monitoring of physical activity (counts steps taken, calories burned, detect inactivity of the body, etc.) and some important medical parameters (such as heartbeat, sleep and waking cycle, etc.). These characteristics on the one hand increase the Perceived Usefulness compared to a traditional watch, on the other hand lead the most sceptical people to consider Smart Watches as excessively intrusive and not fundamental.

Continuing the analysis, many respondents have discussed the phenomenon of “Cookies”: from a technical point of view, cookies are small files containing codes that are sent from a web server (usually a website) to a web client (i.e. a browser used for online browsing). The family of cookies is wide and consists of two macro categories (Galaxies, 2015): technical and profiling cookies. The former in turn can be “persistent cookies” (cookies that remain active until a predetermined date, with the aim of ensuring the proper functioning and security of certain operations such as home banking) or “session cookies” (they are automatically destroyed when the navigation web page is closed). Profiling cookies, on the other hand, are used to track users’ searches and profile them according to their personal preferences: in this way, advertising messages are transmitted to them during navigation in line with their previous research. The analysis shows that the use of cookies can lead to problems of privacy and intrusiveness. With the aim of protecting users, the “General Provision on the Use of Cookies” (Official Gazette no. 126 of 3 June 2014) has prohibited the automatic installation of profiling cookies by website operators without first informing the user and obtaining their authorisation. The “Cookies” category therefore contains the answers of both respondents who have mentioned cookies directly, and those who indirectly refer to them (talking about the customisation service of search engines, platforms such as You Tube and so on).

Although “Online Shopping” websites are search engines that use Cookies, in order to correctly analyse the data, a separate category has been created for these activities. It includes both the e-commerce of physical stores and platforms such as Amazon through which purchases are made.

“Smart home” is a category which consists of two main types of devices: on the one hand there are security systems with Artificial Intelligence, equipped with cameras and sensors directly connected to the owner's phone through an app, which have increased the perceived security and tranquillity of the individuals who own them; on the other hand, there are the so-called “home robots”, i.e. domestic appliances capable of replacing humans in certain household chores (e.g. vacuum cleaners, bread machines, etc.). The latter have registered a high perceived usefulness as they are totally automatized and require the minimum human effort, allowing to save a considerable amount of time and energy.

Few respondents mentioned smartphone specific apps, among which the most important were home delivery service and credit card apps with which mobile payment can be made.
A small number of respondents reported experiences in fully automated shops, labelled as "Shops with AI": these are bars, restaurants, and dressing rooms fully automatized, where human work has been completely replaced by machines and robots.

3.3.2 Categories of Adoption and Rejection

The open-ended questionnaire analysed through the CIT, had the precise objective of evaluating the positive and negative aspects that emerged from the respondents' answers, respectively in a scenario of adoption and resistance to a smart object.
The ultimate goal of my analysis is to identify the macro-categories of adoption and resistance to smart devices, verifying the correspondence or not between the factors that impact them positively and negatively. The process of categorization of the factors has been methodical and iterative, and led to the creation of two main macro-categories, namely "Individual characteristics" and "Smart objects characteristics", divided by valence. These are formed by various sub-categories, which in turn are impacted by both positive and negative factors. The analysis aims to verify the correspondence and specularity of these factors, i.e. the entity with which the drivers that lead the individual to adopt a smart object are the exact symmetrical opposites of the drivers of rejection.
By submitting the positive and negative scenario of the smart object adoption to the same respondent, allowed a comparative analysis of the responses, leading to a first main conclusion: out of a total of 61 respondents, only in 17 it emerged that the rejection factors were exactly the opposite poles to the adoption factors, while 43 respondents provided different and non-specular positive and negative motivations. This finding confirmed the validity of the research question of the analysis, demonstrating the need to consider the barriers of resistance to smart objects as separate categories and not necessarily as opposed to those of adoption.

3.3.3 Individual Characteristics

The macro-category of "Individual Characteristics" contains within it the psychological factors and individual features that lead consumers to form their own positive or negative perception of smart objects. With reference to the distinction between primary and secondary attributes (Moore and Benbasat, 1991) discussed in Chapter II, I decided to base the macro-category of "Individual Characteristics" on secondary attributes, i.e. considering the individual perceptions of the attributes of smart objects, rather than the device objective characteristics. This category was particularly significant both in the process of adoption and rejection of smart objects, as more than half of the respondents were affected both positively and negatively. In turn, this macro-category is formed by five sub-categories that have a positive and negative impact on the smart object adoption process.

Perceived Value

The “Perceived Value” of a device refers to the individual's assessment of the value of the smart object, including both monetary and utility dimensions. Ram and Shets (1989) introduced the “Value barrier” among the functional barriers that lead consumers to reject Innovation: the perception of a valuable price-performance ratio of the innovative product is necessary for consumers in order to adopt it. As will be demonstrated by the results, it is also necessary that the Perceived Value is greater than the substituted products’ one. Specifically, this category is influenced by four factors: Perceived Usefulness, Relative Advantage, Perceived Price, Perceived Complexity and Perceived Ease of Use.

Perceived Usefulness

“Perceived Usefulness” refers to the benefits that consumers think to gain by using the IoT product, increasing the efficiency and/or effectiveness of the performance of their tasks.

The findings reveal that more than half of individuals perceive the positive utility of smart objects, especially because these devices enable users to save time or energy:

- Time saving: time is a scarce and fundamental resource for human beings, and an object that allow individuals to minimize it in their activities is perceived as highly useful and valuable: *“The vacuum cleaner saved us time and effort every day. In fact, instead of vacuuming early in the morning we can sleep a little more or do other tasks at home”* (Montpellier). Among the various services, the personalisation of search engines and profiling cookies was found to be very useful: “*I felt relief since I have saved a lot of time because, thanks to Youtube's suggestions, I didn't have to search manually*”.
- Energy saving: the analysis showed that users perceive as useful objects that perform actions in their place and that allow them to save energy: “*It is a satisfaction to come home and know that the work I should have done was done by someone else in my place, or rather, something else*” (Turin). In general, these are objects that simplify people's daily activities by allowing them to delegate what they had to do on their own before: "*I was really impressed by the things that a small electronic object (like Google Home) can do, saving you time or even simply not getting up from the sofa or bed*”.

Findings indicate the polarization of Perceived Usefulness, which was also detected as a rejection factor by many respondents who reported the inutility and non-essentiality of smart devices: “*I don't think Siri's help is useful: I deactivated it immediately, I didn't care to have it and I don't regret taking it away*" (Jakarta).

Relative Advantage

The assessment of any product or service involves the consumer comparing it with the product or service that it would replace. “Relative Advantage” refers to the advantage deriving from the adoption of the product, compared to the previous one that is being replaced.

It emerged as a factor which acts both as a positive and negative driver of adoption with the same intensity: on the one hand, respondents decided not to buy the smart product because its features were not perceived as “new”, but implemented in the devices they already owned: “*I realized that buying it just to wake me up,* *translate languages or perform mathematical calculations, would have been a waste since these activities are easily performed from my smartphone*" (Cerveteri); on the other hand, the same number of interviewees stated they found advantages in using the smart device over the existing product, thus increasing its Perceived Usefulness and in general its Value.

Perceived Price

Although the price itself is an objective numerical value, for the purposes of the analysis it is necessary to consider the "Price Perceived" by the single consumer: every user perceives price differently according to various personal factors such as economic availability, the immediate need for the product and so on.
The "Perceived Price" acts both as a positive and negative driver of adoption, revealing a not so significant degree of polarization: on the one hand, it has negatively influenced the consumers who found a lack of monetary value for these devices because of the too high and unsustainable price; on the other hand, it had a positive impact on respondents, who perceived a monetary advantage in the purchase, considering the price of these devices convenient.

Perceived Complexity and Perceived Ease of Use

"Perceived complexity" and "Perceived Ease of Use" are two specular sides of the same coin: the former is intended as the individual's difficulty both to comprehend and implement an innovation (Rogers, 1962), while the latter is "*the degree to which using a particular system would be free from effort*" (Davis, 1989). Findings suggest a perfect correspondence between the two drivers, but a greater positive relevance of Perceived Ease of Use: simplicity, immediacy and comfort of use positively affect the intention to adopt of respondents, while "Perceived Complexity" influence negatively few interviewees.
Both factors influence the "demographic variable": on the one hand, mature respondents (over-55 years old) tend to perceive a greater complexity in the use of smart objects, and this increases their scepticism and attachment to traditions, thus raising barriers of resistance ("*The choice not to domotize the house was taken by my father. Mental closure? I don't think so, it is a generational issue that follows a cognitive process different from that of the millennials. A concrete example: the first time my grandmother read a digital newspaper on an iPad, she wetted her fingers to turn the page*", Bucharest); on the other hand, smart objects are perceived as solving problems typical of the more mature age groups, thanks to their simplicity and immediacy of use: "*My grandfather can no longer use his mobile phone effectively, so in times of difficulty simply saying a few words, the device put in contact my grandfather and his daughter*" (Lisbon).

Smart objects' features affecting Perceived Values

The distinctive features of IoT devices have a strong impact on the Perceived Value of the user.
First of all, the smart objects' "Multifunctionality" increases the Perceived Usefulness for a considerable portion of respondents: the ability to perform many different functions on their own creates the so-called

"All in one" effect, which leads to an increased Perceived Value of the single device: "*I didn't feel I had just changed phones, I felt I had purchased additional services for my daily life that I would need a lot*" (Tivoli). The second feature that impacts the Perceived Value is the "Interoperability": as already discussed, it is the ability of smart devices to be used together, interacting with each other in order to create a positive synergy that increase the functionality of both paired devices ("*Alexa is able to interact with the environments of the house: it can manage connected devices such as lights, radiators, cameras, locks, video intercoms*" Rimini). The impact of Interoperability on the Perceived Value is both positive and negative: on the one side, some respondents declared to perceive an increased Usefulness of the interoperable device, being positively conditioned in the purchase (*"The integration with the Google assistant is very useful: I can move the view from my smartphone to my TV at any time, which is very useful while cooking for example",* Trieste); on the other side, other respondents see Interoperability sceptically, as a negative adoption driver ("*This was not seen by me in a very positive way, I thought it was exaggerating. I believed that all these functions, although they facilitate the human work, are also destroying them*" Rimini).

some of the individuals who perceived this characteristic negatively explained that to fully exploit the usefulness of the smart product, the device itself is not enough, since it requires other objects to be connected: "*I thought that this product was not completely useful, but it would be if I had other elements at home that could communicate with it*" (Portland). This affects negatively both Perceived Usefulness and Perceived Price, because in addition to the purchase of the smart object it is necessary to sustain additional expenses for connectable accessories to fully benefit of the functionalities: "*Despite the advantageous price, in order for the experience to be complete, I would have had to equip my house with smart plugs on all appliances and systems. Making a careful quantitative evaluation, I concluded that it would have been an unsustainable expense*" (Zagreb).

At least, the smart objects' ability to customize the offer for the single user has a positive impact on the Perceived Value: a considerable amount of respondents declared to be satisfied with the personalised service offered mainly by online streaming and shopping platforms, indicating it as an adoption driver ("*Netflix recommends content according to my preferences and habits: I felt a sense of satisfaction that I found content of my favourite genre*", Brussels). Thanks to custom recommendations, users feel understood and known by the platform and this leads to a double consequence: firstly, it enhances the empathic relationship between user and device; secondly, it increases the Perceived Usefulness of the platform itself, as it allows users to save time and energy that they would have spent to select the content to see, listen or buy ("*The first time I used it I spent a lot of time looking for the products I needed, but thanks to AI on my second purchase, my shopping cart was saved making it easier and faster*", Wellington). Only few respondents indicated personalisation as a factor against the adoption: they found it unsatisfactory and decided to give up the purchase of the service/product.

Perceived Security

The "Perceived Security" category includes factors that positively and negatively impact on consumers' perception of smart devices' reliability and safety, and consequently affect the process of adopting or rejecting the device.

Perceived Reliability and Perceived Risks

From the analysis emerged that large portion of respondents were positively influenced in their adoption choice by the "Reliability" and credibility of smart objects: this factor especially emerged with regard to home automation systems that "*are able to provide information and a sense of security that was impossible to achieve before*" (Paris). A high Perceived Reliability derives mainly from the smart objects' ability to provide a real-time monitoring of the external environment, increasing the user sense of control.

The negative pole of "Perceived Reliability" is represented by risks involved in the device adoption. Risk barriers have been introduced by Ram and Shets (1989) and arise when the potential adopter is unable to assess the risks and uncertainty associated with the adoption of the new product from a financial, functional and social point of view. The findings show three types of risks:

- Functional risk: it refers to user's fear that the smart object has functional bugs and will not function properly ("*I did not buy it for fear that it could turn into a disadvantage and no longer into a help, which could cause damage in my apartment, such as ruining the floor or breaking something that its sensors failed to detect*", Marino).
- Physical risks: it is the perceived risk associated with potential damage to the individual's health using the new product. The analysis revealed that some respondents have perceived it for two reasons: firstly, the object is permanently connected to the network and it leads users to be sceptical about the dangerousness of the emitted radiation: "*My mother said that wearing this object on the wrist fixed and continuously can be harmful to health, emitting potential radiation*" (Sofia); secondly, the automatism of such devices and the lack of human control, raises doubts about the reliability of the correct functioning that, in the worst case, can damage health: "*The power of AI systems, if misdirected, could be very dangerous. Think of the cyclist invested and killed last March in USA by a driverless car of Uber. The driving system has failed to correctly identify and classify the victim as a person on a bike*" (Vilnius).
- Persuasion: it is the smart devices' ability to alter the users' perception of other objects or situations. This factor negatively influenced the intention to adopt of respondents: "*Using a 50 euro banknote, allows you to perceive the "sacrifice" of spending money, while the digital purchase, not involving a physical exit of money from our wallet, makes spending almost unconscious*" (London).

Trialability

"Trialability" is "*the degree to which an innovation may be experimented on a limited basis*" (Rogers, 1962), and resulted as a significant factor in the formation of the intention to adopt a smart object: both in the

positive and in the negative case, by testing the product before purchasing it, individuals become familiar with the new device, reduce the Perceived Risk arriving at the decision moment more consciously.
From the analysis, respondents had formed on the one hand a negative perception of the product after testing it for free, considering it not useful or not in line with their needs; on the other hand, Trialability acted as a positive driver of adoption.
Considering Trialability as the possibility to try the smart object for free for a limited time before purchasing it, it emerges that it is mainly a necessary factor to avoid resistance to innovation: a relevant amount of respondents reported the "Lack of Trialability" among the motivations for which they did not adopt a smart object. Among these, interesting is the positive correlation between scepticism regarding online purchases and product Trialability: "*I was very sceptical about the fact that the site could identify the best size for my body. Not being fully convinced of the size suggested I preferred to proceed with the traditional purchase in store to be more certain*" (Istanbul). In fact, respondents have often stated that they prefer not to buy products online because "*prefer to test the products before purchasing them*" (Ciampino).

Visibility
Moore and Benbasat (1991) firstly introduced the concept of "Visibility", defining it as "*the degree to which it is possible to observe someone else using the innovation*". According to this definition, throughout the analysis the concept of Visibility has repeatedly emerged both as a driver for and against adoption of smart objects. In fact, these are cases in which respondents had the opportunity to either see someone else using the product or attend a demonstration in the store: this has contributed to have a direct contact with the product, creating a positive or negative perception of it. The analysis revealed that Visibility had a crucial positive role for some respondents: by observing the benefits of the products in practice, users have decreased the degree of Perceived Risk, increasing the security of their choice.
This factor does not show any polarization, as the analysis did not reveal a negative counterpart.

Traditions Barriers and Drivers
Among the psychological barriers of the Ram and Sheth model (1989) the "Tradition and Norm barrier" indicates the individuals' resistance to adopt because the innovation is not in line with their daily routines, habits and traditions. In the analysis, this category refers to the smart objects consistency with the users' pre-existing habits and passions, thus considering the compatibility of the device with values and traditions. Findings on the one hand confirm the users' attachment to their status quo, erecting the "Incompatibility" barrier; on the other hand, a new driver to the adoption of such devices has emerged, being able, through their use, to create "New Habits and Traditions", entering the daily routine of the user.

Incompatibility and New Habits and Traditions
Compatibility has been defined as "*the degree to which an innovation is perceived as being consistent with the existing values, past experiences, and needs of potential adopters*" (Rogers, 1962). In accordance with

this definition, most respondents have declared not to have adopted a smart device because of its Incompatibility with their pre-existing passions or habits. More deeply, on the one side it resulted that respondents had a strong attachment to "pre-existing passions" that the adoption of the smart object would replace: "*My feelings were contradictory: the central problem is that I am passionate about and studious of analog watch mechanisms. I felt confusion and fear of losing my passion*" (Bucharest); on the other side, the influence of "pre-existing habits" emerged for other respondents, since the adoption of smart objects would have led individuals to change their routines, traditions and established beliefs ("*I did not buy the product because I am convinced that cleaning the house traditionally rather than leaving it to a machine can provide a deeper cleaning*", Marino).
The positive counterpart to the barrier of Incompatibility, is the creation of "New Habits and Traditions" thanks to the use of smart devices: "*If we consider that I use the service practically every night, it has now become a real tradition. Some nights with Netflix I even fall asleep*" (Matera). The creation of "New Habits and Traditions" reinforces the relationship between individual and smart object, as the latter has become part of user's daily life, thus positively influencing the adoption and use of such innovative objects.

Image Category

"Image" refers to the perception of the consequences of the smart object adoption on the individual social condition. This concept has been already introduced in literature as "*the degree to which using an innovation is perceived to enhance one's image or status in one's social system*" (Moore and Benbasat, 1991).
The analysis show that 3% of respondents were induced to adopt a smart object by social considerations: on the one hand, social influence is a clear positive driver, since consumers consciously adopt a smart object in order to enhance their social image ("*Having the I-Phone consecrated my entry into the social class of those who have this phone brand*" Johannesburg); on the other hand, social influence can be more hidden and unconscious, in cases where consumers are driven to buy a product only to comply with the canons of fashion ("*When asked why she bought it, she replied -I don't know, everybody has it-"* Verona).
Results indicate that the social factor emerged only as a positive driver, as there was no perception of a "lowering" of the social image due to the adoption of smart objects. Therefore, in this case there is no polarization of the factor.

Psychological Traits

Considering the "Psychological Traits" as stable characteristics of the individual's personality that lead to different dispositions to act, relatively independent from the changing context, the relevance of this category emerged throughout the analysis. Confirming what had already been said (Touzani et al., 2017), findings show that a relevant amount of respondents were influenced by their psychological traits when deciding whether or not to adopt a smart object.
This category deals with the individual's personal perception and relationship with Innovation, which leads to the definition of two opposing types of users: Sceptics and Innovators. On the one hand, "Innovators" are

individuals with a natural propensity for technology and smart devices' adoption, on the other "Sceptics" are those users who distrust Innovation and tend to perceive it with suspicion.

While the perceived enthusiasm towards smart objects has been scarcely mentioned by respondents (*"I've always been passionate for everything that is technological since technology, in many ways, simplifies the individual daily life"* Swansea), a relevant amount of them confirmed the existence of strong barriers to the adoption of innovation, declaring themselves sceptical.

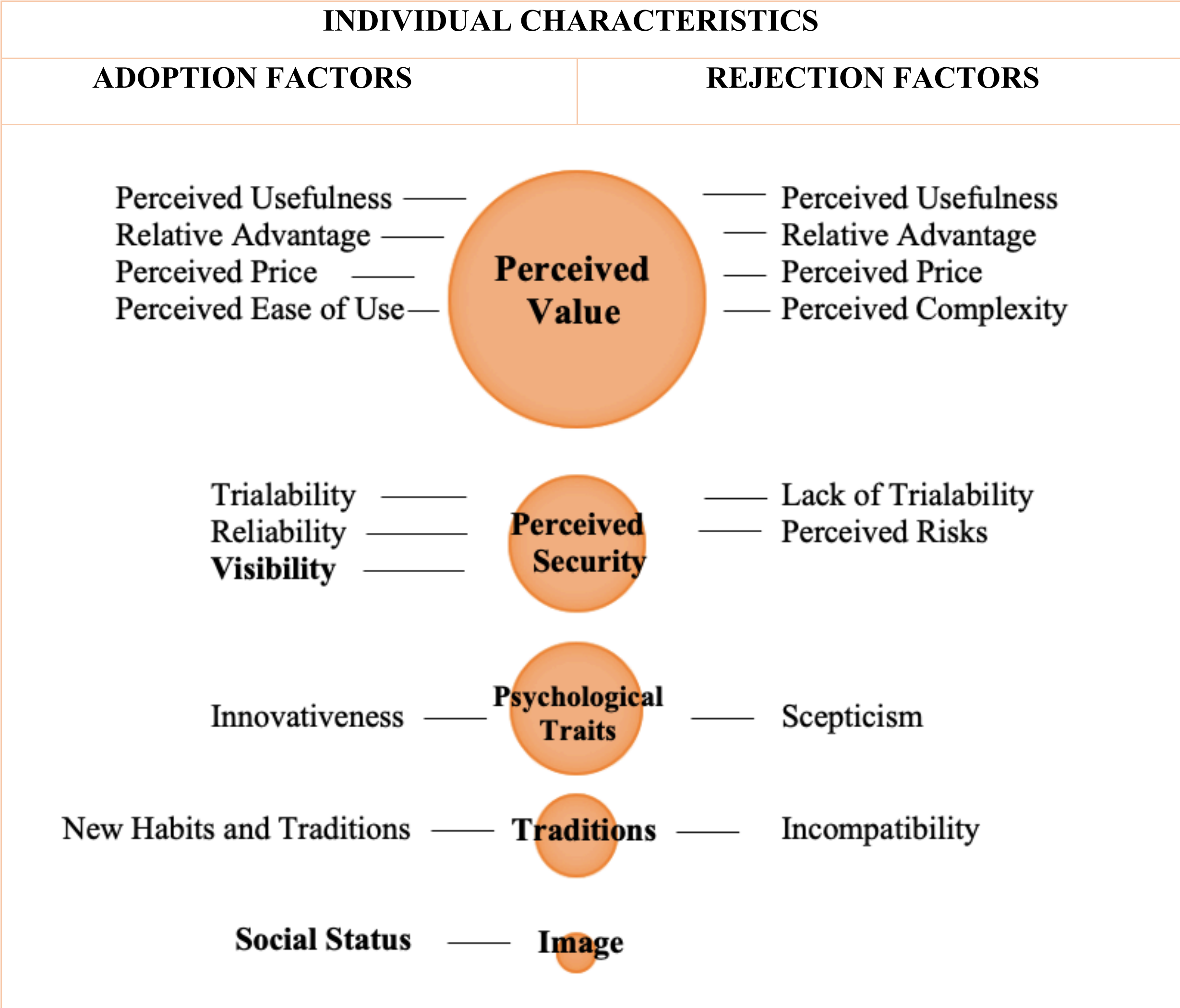
Scepticism may result from various reasons: beliefs and judgments about oneself ("*Awareness of being a person who interacts little with these devices*" Brussels); fear of novelty and lack of confidence with innovation ("*I didn't buy it for fear of novelty. [...] The little trust I placed in this kind of service by dwelling more on the negative sides*" Marino); strong attachment to traditions and habits ("*As soon as he saw Roomba, all the scepticism typical of those who do not have and do not want to deal with intelligent services appeared, remaining attached to old habits*" Reykjavik), fear of Intrusiveness ("*At first I was sceptical, it seemed to me an interference in my daily life*" Matera) or doubts about the device actual functionality ("*I was certainly a little sceptical to think that it could really work well*" Rimini).

Moreover, it emerged that Scepticism is fueled by a feeling of independence of those individuals who prefer to perform tasks on their own, not appreciating an object acting in their place: "*I think I am able to do a search on my own, call, send messages and so on, without the need for Siri. [...] I was a bit annoyed, as if the phone felt that I needed the help of a digital assistant to do normal operations*" (Jakarta).

While Innovativeness always leads to adoption, Scepticism does not always lead to rejection: in fact, five respondents stated that they adopted the object despite the initial Scepticism, and that they were positively satisfied with it (*"I was definitely surprised, because I have always been very sceptical about devices of this type. I'm happy with my purchase and the fact that it has "implemented" and made my daily life a little more digital"* Mumbai). These findings allow to conclude that the mistrust of innovative products often comes only from prior beliefs about it, and that resistance barriers to smart objects may be overcome through the use of the device in first person: "*I've never been passionate about high technology but I have to admit that since I put it on my wrist I haven't been able to get rid of it*" (Sarajevo).

The following map contains a visual representation of the subcategories belonging to "Individual Characteristics": with the aim of allowing to perceive the relative importance of each set of factors, every category has been represented in a visual way through the size of the circle in which it is inserted.

The map also highlights the unidirectionality of "Visibility" and "Social Status", as they do not have the corresponding negative driver.



3.3.4 Smart object Characteristics

"Smart object Characteristics" is a macro-category which involves the innovative features of smart devices (i.e. Connectivity, Intelligence and Ubiquity) and their consequences in the consumers' process of adoption and rejection. The need to create this category is due to the peculiarity of smart objects compared to the conventional ones, which have generated new adoption and rejection drivers.

This macro category is composed by two subcategories, namely "Technology Vulnerability" and "Communicability".

Technology Vulnerability

The category "Technology Vulnerability" has been introduced by Mani et al. (2018) in order to consider the impact of new variables typical of the digital age on the process of adoption and rejection of an Innovation. The new features of smart objects (Intelligence, Connectivity and Ubiquity) provide them with new abilities, distinguishing "smart devices" from "non-smart" products: these new features modify the relationship between user and smart device, creating new adoption and rejection drivers that did not exist with regard to ordinary objects.

Intelligence

“Intelligence” is intended as the smart objects ability to be autonomous and undertake actions based on previously captured data (Mani et al., 2016). Performing actions without human intervention is one of the characteristics that most distinguish "smart" objects from the traditional ones, and that enable them to assume anthropomorphised characteristics.

The analysis has shown that the device’s Autonomy is a polarized factor, since emerged both as a positive and a negative driver of adoption.

On the one hand, Autonomy has been identified as a positive driver by respondents who have been satisfied with the ability of the smart device to perform actions without their involvement, allowing them not to control the whole process, saving time and energy, and increasing the Perceived Usefulness: *“The domestic robot does everything in perfect autonomy! The only two efforts required are: pressing the start button and emptying the dust bag when the work is finished*” (Turin). Moreover, the device bases its future actions on previously captured data, so that it can even anticipate the user's needs: “*Without me manifesting the needs, it acts autonomously predicting my needs on the basis of my routine*” (Ciampino).

On the other hand, Intelligence has created a barrier for some users who perceive the fear that automatized devices will definitively replace human work, perceiving the concern of the increasing unemployment due to the presence of robots: “*How far will we go? Will home automation really replace human work completely?*” (Turin).

Continuing the analysis, the total Autonomy is a negative driver to adoption as it brings out the Scepticism of users who perceive the need for human intervention: *“I do not totally trust something that can do everything autonomously”* (Marino). It is a lack of confidence in new AI technologies, which results partly from a lack of information, partly from an attachment to the way in which people are used to perform certain tasks and jobs: “*I have been wary of the fact that a 'machine' could have performed certain types of housework independently without any help, as thoroughly as an individual could have done*” (Reykjavik).

The “Lack of human interaction” is a concept already treated in literature as “the importance of human interaction to customers” (Dabholkar et al., 2002). According to this, the analysis show that the absence of humans social presence is negatively perceived by consumers: “*In the long run if robots become part of our everyday life it could become a factor against the restaurant, since going to the restaurant means pleasure, feeling pampered in a warm environment, condition that can only be met by human empathy*” (Turin).

The positive counterpart of the “lack of human interaction” factor is the new relationship established between smart device and user, perceived as adoption positive driver by many respondents. The smart objects Autonomy in acting makes them anthropomorphised, thus changing the relationship with human beings, which is now more intimate as the user feels “understood” and “well-known” by the object. The device becomes a real friend as it suggests what to do, remembers appointments, answers questions and performs actions in the place of the individual: “*Siri and I have become a single thing. Every day I ask Siri to set my alarm clocks, to remind me of them and to set appointments. Every time I have to call someone, I* *ask Siri. By now, the phrases I say most often on a day are "Hey Siri! Call X!". Siri is like a friend of mine, reminding me schedules and things to do. By now without Siri I can no longer imagine myself*" (Rennes).

Connectivity, Ubiquity and Privacy Issues

"Connectivity" refers to communication protocols that allow smart objects to exchange information and communicate with the external world (with other objects, servers, entities, and so on) thanks to the internet connection (Mani et al., 2016). In accordance with this definition, the analysis revealed that respondents perceive the consequences of Connectivity with regard to Privacy Issues.

As discussed in previous Chapters, the Privacy factor has been widely debated and is considered one of the main barriers of resistance to smart objects. Connectivity allows devices to communicate with each other and exchange gathered information, leading to two fundamental Privacy issues: on the one hand, individuals do not have control over the amount and the nature of data captured by the device, incurring the risk of disclosing sensitive information; on the other, collected data may be transmitted without individuals' permission, as they do not have control over third parties' access to such data. Moreover, there is also the problem of Hacking, i.e. the risk of illegal intrusion by third parties into the IT systems in order to steal private information. This factor increases the Perceived Risk for the user and the perception of Intrusiveness, enhancing the resistance to adopt: "*In case of hacking this data could be sold or disclosed to third parties who could use it for incorrect purposes and without my knowledge*" (Portland).

The lack of control over personal information and the lack of permission for its transmission to third parties is perceived as a strong barrier to adoption by a relevant number of respondents: "*I was afraid that the dialogues with Siri would be heard by third parties. I felt insecure and I thought that the Privacy issue is fundamental for me: most likely, if I had been sure that the conversations were private and protected, I would have acquired this technology*" (Monchengladbach).

The third innovative feature of smart products is Ubiquity: it refers to the ability of such devices to be used anywhere and at any time. The analysis has shown that this characteristic has a negative impact on consumers' adoption intentions, leading to Privacy issues. A significant amount of respondents stated that they have perceived the so-called "Big-Brother effect", being "controlled" by smart devices, and it led to a sense of discomfort and irritation: "*I felt controlled, and it scared me because I felt under observation*" (Bangkok). Ubiquity is therefore perceived as a significant invasion of personal Privacy, and consequently as a barrier to adoption.

A negative driver that derives from the characteristics listed above is Intrusiveness, as devices: a) communicate with each other by transmitting data through the Internet (Connectivity); b) are able to perform actions without the user's permission (Intelligence); c) can be used in any place and at any time (Ubiquity). Referring to Intrusiveness as "the ability of smart objects to enter the users' daily life without their permission and with insistence", it emerges from the analysis that it is a negative driver for adoption, mainly impacting the Privacy Issue. In fact, it is commonly recognised in marketing literature that Intrusiveness leads the consumer to experience negative feelings of frustration, irritation and nervousness that increase the barriers to adoption. The Intrusiveness of these devices is therefore negatively perceived by many respondents, who have been annoyed by the insistence of smart devices: "*Firms do not care about the intrusiveness that these systems bring with them, often arouses frustration in consumers. I consider cookies very often invasive, almost controlling, of our online research path, as if there is always some company near us willing to do anything to gain a consumer*" (London).

Communicability

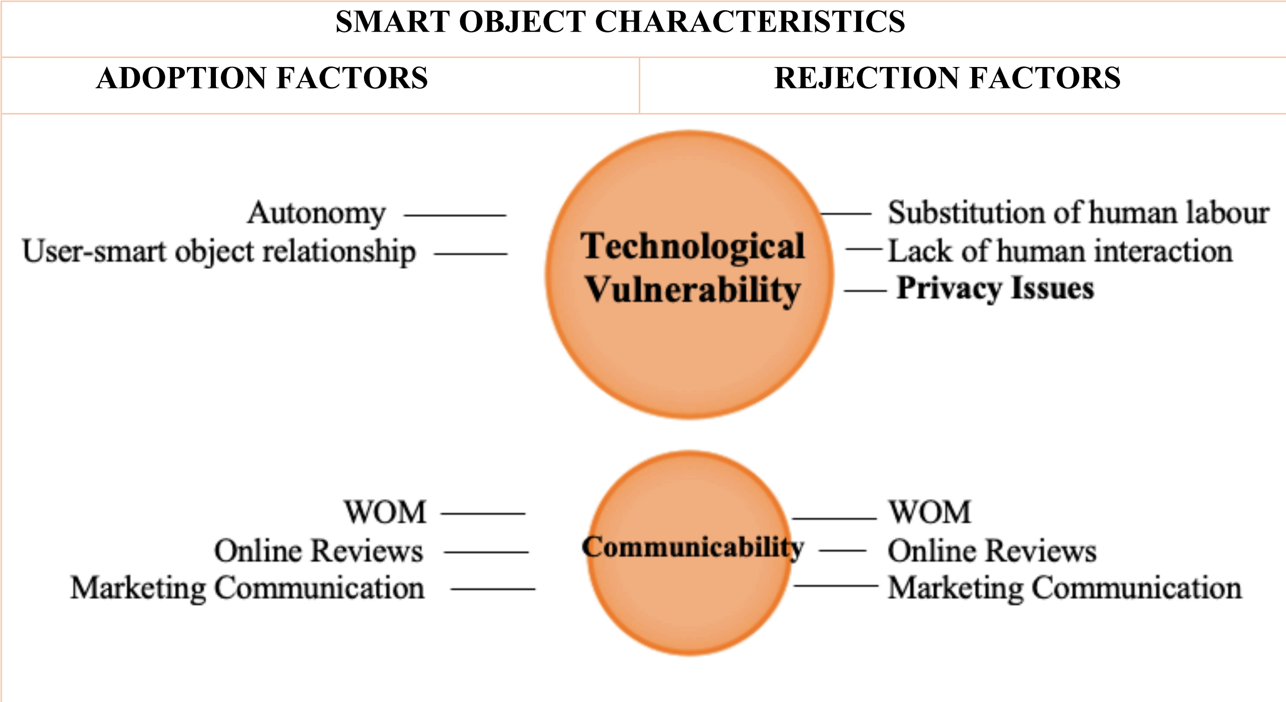
With the term "Communicability" is intended the whole communication around the product, implemented both by marketers and consumers. "Communicability" represents a distinct category, since it is able to influence consumers' opinion on a specific product, leading them to adopt or reject it: more deeply, 21% of respondents have been positively affected by smart objects' communication, while only 6,5% have been negatively influenced.

Basically, Communicability is impacted by three main factors:

- Word of Mouth, intended as the phenomenon whereby consumers who have already tried the product in first person, voluntarily describe their experience to other potential customers (usually friends or family), influencing their intention to adopt either positively or negatively. This driver was more significant as a positive driver in the positive scenario, while few respondents said to be negatively influenced by WOM and decided not to adopt the smart object for this reason.
- Online reviews**,** namely other consumers' opinions about their personal experience with a certain product released publicly online on forums or information sites. In general, this type of communication is considered highly credible and reliable as these are objective and disinterested reviews, not directed by marketers. This factor equally influenced respondents both positively and negatively;
- Marketing communication, namely communications provided by the company aimed at increasing product awareness and influencing the consumer purchase intention. These are communications (often by email or notification) with the purpose of implementing a precise marketing strategy, that resulted in a positive impact on respondents: the majority of respondents reported to have been positively affected by it, while few of them have declared to be negatively affected and annoyed, perceiving it as too persuasive: "*I felt induced to choose only between certain products*" (Bangkok).

The following map contains a visual representation of the subcategories belonging to "smart objects characteristics": with the aim of allowing to perceive the relative importance of each set of factors, each of them has been represented visually through the size of the circle in which it is contained.

The map also highlights the unidirectionality of "Privacy Issues" as they do not have the corresponding positive driver.



3.4 Results Discussion

With the aim of identifying the categories pro and against the smart objects adoption, and to verify if the negative factors that drive the rejection are the specular opposites of the positive ones that motivate the adoption, a sample of 61 respondents has been analysed with the qualitative method through the Critical Incident Technique.

First of all, the results show a greater use of AI services compared to AI physical products, due to the intangible nature of AI services that leads individuals to make use of these algorithms without being fully aware of them. The services and products emerged from the analysis have been divided into ten categories according to their nature and use, in order to study their presence: the findings show that the most widely used devices are Voice Assistants, followed by Streaming Online services, Smart Watches and all the others. The questionnaires analysis revealed a branched categorization of the factors: the two main macro-categories identified ("Individual characteristics" and "Smart objects characteristics") contain various sub-categories, which in turn are impacted by positive and negative adoption drivers. In accordance with Ram's model (1987) and in line with other previous studies (e.g. Mani et al., 2018; Ram and Sheth, 1989) the distinction between "individual characteristics" and "smart objects' characteristics" has been confirmed. This categorization adds to the previous literature the distinctiveness of smart devices' features compared to traditional objects, i.e. Autonomy, Connectivity and Ubiquity: it was found that these characteristics are not neutral for consumers, instead they condition the evaluation of the device, creating new positive and negative drivers for adoption.

Comparing the results the two macro categories, it has been found that "individual characteristics" have a significantly higher impact on consumers' adoption process compared to "smart objects' characteristics". More deeply, the polarization within the both the macro-categories appears almost perfect, as the presence of resistance barriers and positive drivers is equal. Hence, it can be concluded that at the "macro" level the magnitude of adoption and resistance factors is approximately equal for both categories.

According to the analysis of the macro-categories, it emerges the identification of 13 positive factors on the adoption of smart objects: each of them presents the corresponding negative driver that acts symmetrically on the resistance to these devices. However, it is not possible to generalize that each positive adoption driver has its negative opposite pole of resistance, as it has been identified the presence of 3 factors (i.e. Visibility, Social Status and Privacy Issues) that instead act unilaterally (respectively the first two are drivers with only positive impact, while the last one is a negative deterrent factor).

Confirming the strong consumers resistance to adoption, the sub-category of "Psychological Traits" emerged among the "individual characteristics". This term refers to the personal stable characteristics which strongly impact the perception and relationship with Innovation and smart objects. Two predominant psychological profiles have been identified, confirming what already said in the previous literature (Touzani et al., 2018). On the one hand, the "Innovativeness" are individuals who are passionate about technological innovations and are naturally inclined to adoption; on the other, the "Sceptics" are users who are distrustful of innovation and novelty in general. Scepticism derives from several factors, among which there is a strong attachment to traditions, fear of novelty and a strong perception of the risks associated with adoption. The significant majority of Sceptics compared to Innovators is a sign that consumers have still difficulty in completely comprehending the value of Artificial Intelligence products, confirming the existence of strong diffidence and individual barriers to the adoption of smart objects. This evidence confirms the importance of studying and comprehending the negative factors that form such barriers, in addition to those of adoption.

The category that most impact the process of adoption is the "Perceived Value" of the smart object: considered in the previous literature just as a barrier (lack of monetary and performance value of the innovation), the results indicate its role also as a driver pro adoption. Among the factors, Perceived Usefulness is the most impacting one both positively and negatively: on the one hand, using the device enable to save time and energy, thanks to the typical smart objects features of "Personalization", "Multifunctionality" and "Interoperability"; on the other hand, some respondents declared to consider the such objects as non-essential nor useful. "Relative Advantage", "Perceived Ease of Use/Complexity" and "Perceived Price" are three polarized drivers which impact both positively and negatively the smart devices Perceived Value. Hence, to confirm the difference in the Innovation adoption process between young and mature consumers, the "Demographic Variable" has been detected: mature generations on the one hand perceive the lack of value of smart objects (due to the high perceived complexity and attachment to pre-existing traditions and habits); on the other hand, they consider smart objects as a tool able to meet their needs, thanks to their multifunctionality and ease of use.

The second category belonging to "individual characteristics" is "Perceived Security" which is almost equally polarized, generating the same amount of adoption factors and resistance barriers. Among the factors, Trialability on the one hand affects this category positively, thus confirming the theory of several scholars (e.g. Johnson et al. 2018; Arvidsson, 2014) who compared the adoption process to a "learning experience" (i.e. the more individuals interact with the product before buying it, the more confident they become, increasing Perceived Security). On the other hand, "Lack of Trialability" is the opposite negative pole, as emerged that Trialability more than being a driver pro adoption, is a necessary factor to avoid resistance: in fact, it emerged scepticism and diffidence towards purchasing process that do not enable consumers to try or see the product before buying it (such as "Shopping online").

Finally, the the "Tradition" category already identified in previous literature (Ram and Shets, 1989) is confirmed. The smart objects' lack of consistency with the "existing values, past experiences, and needs of potential adopters" (Rogers, 1962) brings out the resistance barrier of "Incompatibility": in particular, the strong individuals' attachment to pre-existing passions and habits has been perceived as a barrier. On the contrary, it emerged that traditions do not act only negatively, since the creation of "New Habits and Traditions" through the use of smart objects has often been mentioned as a positive driver of adoption. So, in addition to the importance of compatibility with existing traditions, the object ability to settle into the user's habits is also relevant.

As already mentioned, the second macro-category is the "smart object Characteristics", made up of two sub-categories: on one hand, "Communicability" is the communication around the smart device (WOM, Online Reviews and Marketing Communications) which both negatively and positively influences the process of adoption; on the other hand, "Technology Vulnerability", already introduced by Mani et al. (2018), refers to the new drivers and barriers of adoption that did not exist before the introduction of IoT, deriving from smart devices' features (Intelligence, Connectivity and Ubiquity). This category creates resistance barriers for a significant amount of respondents. In this regard, the Autonomy of smart objects leads on the one hand to an increase in Perceived Usefulness, as devices replace humans in many actions and tasks; on the other hand, the tendency of objects to replace the individuals' work and the lack of interaction with human beings, increases scepticism and distrust of some users. Finally, thanks to the new anthropomorphised characteristics of these objects, the user-device relationship has changed: individuals interact with the object, feeling understood and building a more intimate and empathic relationship with it.

Up to this point, the factors that have been described are the ones which present both the positive pole and the negative pole of adoption. Significant results regarding the non-speculiarity of adoption and rejection drivers have been achieved through the comparative analysis of the positive and the negative scenario experienced by the same individual: out of 61 respondents, more than half motivated the rejection of these objects with different and not symmetrical factors to those given for the adoption.

In general, three factors have been identified that impact the adoption process in a unidirectional sense, thus not presenting the opposite counterpart. The well-established belief in literature that it is sufficient to analyse just the positive factors of adoption since the resistance ones are merely the opposites, has therefore been contested by results, pointing out the need to better comprehend the barriers of resistance as well as the drivers of adoption. Specifically, on the one hand, the results reveal the "Visibility" and "Social Status" factors, belonging to the "individual characteristics", which only have a positive impact on the adoption of smart objects, since no respondent has reported to have perceived these drivers as resistance barriers; on the other hand, the "Privacy Issues" (belonging to the "smart object characteristics") act solely as a deterrent to the adoption of smart devices, since no category representing its positive opposite pole has been identified. Privacy Issues therefore only have a negative impact on the adoption, as no positive factor has emerged that would make consumers perceive protection and security in the processing of their personal data. Privacy Issues arise from the objects ability to interact with each other (Connectivity) and to be used in any place and at any time (Ubiquity): users lose control over the nature and amount of personal information captured by devices and over the transmission of this data to third parties (therefore perceiving the risk of Hacking). In general, the analysis conducted has given relevance to the barriers of resistance raised by consumers to the adoption of smart objects. In particular, the findings suggest that an important factor causing innovation failure is consumer resistance, as scepticism is still high and barriers of resistance as well.

Managerial Implications and Research Limitations

The future of the human being will be increasingly pervaded by the innovativeness and ubiquity of devices equipped with IoT. The benefits brought by such devices are not always comprehended and accepted by consumers, who are sceptical and erect barriers of resistance. In order for IoT to effectively grow and deliver its benefits to the various stakeholders, these barriers of resistance need to be removed.

The findings show that at a managerial level it is increasingly necessary to implement policies and strategies to destroy these barriers of resistance by making individuals understand the real potential of these devices. Moreover, the results obtained about the unnecessary correspondence between positive and negative adoption factors suggest that scholars should continue to study the nature of the barriers, analysing them as distinct and separate category from the positive adoption factors.

In addition, the two macro categories identified ("individual characteristics" and "smart object characteristics") highlight the unique attributes of smart devices that differentiate them from traditional objects: the importance of considering these characteristics in the analysis lies in the fact that these are not neutral for consumers, instead they form new positive and negative drivers of adoption. Specifically, the "privacy" factor assumed particular importance, which is a new negative driver for adoption that did not exist in the context of traditional objects. Furthermore, since it has emerged that privacy is a driver that only acts unidirectionally, i.e. only negatively, it is possible to use this result to continue investigating the nature of this barrier.

In terms of future research, the present study provides a further insight into the field of analysis of resistance barriers, providing relevance to the factors that contribute to their formation, considering them independently from the positive drivers of adoption.

Nonetheless, the present study has some limitations that could be overcome by future research. Firstly, the analysed dataset represents a small sample of the total population, so the same research question can be investigated across a larger and more representative sample.

Secondly, the decision to use CIT analysis derives from the early state of research, i.e. the exploratory stage: future research that would implement a quantitative approach will be useful to determine the magnitude of the barriers of resistance and adoption factors and their correlations.
Furthermore, the results obtained on the "demographic variable" highlight the different approach to innovation according to age: as the survey did not ask the age of respondents, further research could investigate the relationship between age and resistance barriers, identifying the different barriers erected by different age groups.

Conclusions

The importance that the Internet of Things phenomenon has assumed in recent years in many fields and for many stakeholders, and the numerous benefits brought by this new technology, have made scholars focus on predicting its future growth, coming to formulate hyper-positive predictions about the spread of objects connected to the Internet in the coming years. Although the growth of IoT continues to be positive, it has encountered difficulties that have not allowed it to record the expected numbers. In accordance with this and in order to understand the reason for the "slow-diffusion" of smart objects among consumers, my research started with a technical and economic overview of the Internet of Things and smart objects, followed by the economic-financial analysis of the market considering the fields of application of this technology, the stakeholders involved and the growth factors. The Chapter I concludes with significant evidence of the still high failure of innovative products, and the slow growth in consumer adoption of smart objects. Maintaining the focus of the analysis on consumer behaviour, and with the aim of understanding what are the critical incidents that drive them positively and negatively to adopt smart devices, the literature review was conducted in Chapter II: the main models of adoption and resistance to innovative products have been analysed, and then emerged on the one side the main positive drivers that motivate consumers to adopt such products, and on the other side the negative ones, that on the contrary lead consumers to erect barriers of resistance that prevent them from purchasing these devices. The major topic that emerged, is that the previous literature has mainly focused on research and analysis only of positive adoption factors, based on the so-called "Complementary Assumption" (Sutton, 2004): the latter assumes that, since the reasons why consumers *do not* buy an innovative product are the exact opposite and speculative reasons for adoption, it is sufficient to analyse exclusively the positive drivers.
In the light of the analysis of the IoT market trend and of the previous literature, my research has been conducted with the primary aim of identifying the positive adoption factors and the barriers of resistance to smart objects, and then to verify whether or not there is specularity between these two. To do this, it was necessary to consider negative drivers as a category by itself, not dependent or a-priori opposed to the one of positive drivers.
In order to categorize positive and negative critical incidents and to study their relationships, a qualitative analysis has been conducted through the use of the Critical Incident Technique (CIT). The achieved macro-categorization provides the distinction between two macro-categories of factors: on the one hand, the

“individual characteristics”, defined as individual peculiarities that make consumers perceive smart objects attributes differently; on the other hand, the “smart objects’ characteristics”, i.e. the new features typical of smart devices (Autonomy, Intelligence, Ubiquity) that make the individual vulnerable to this technology. The main contribution of this categorization to the previous literature (which already distinguished between “individual characteristics” and “product characteristics”) is to highlight the revolutionary characteristics of smart objects compared to traditional ones, capable of creating new adoption and rejection drivers that did not exist before. These two macro categories in turn contain both positive and negative factors of adoption, among which the relationships have been studied.

The results obtained from the analysis are in contrast with Complementary Assumption (Sutton, 2004), rejecting the a-priori correspondence of the positive and negative adoption categories, for two main reasons: firstly, through the comparative analysis of a positive and a negative adoption scenario of the same individual, out of 61 respondents more than half have given reasons for adoption that totally differ from those for rejection. Secondly, three factors were identified that act unidirectionally on adoption, of which two impact only positively (Visibility and Social Status), and one only negatively (Privacy Issues). This means that no respondents reported to perceive the Visibility of the smart object as a barrier to adoption, nor to perceive a lowering of their social role due to the adoption of such devices; similarly, no “protection and confidentiality” factor in the processing of their personal data was recorded, thus perceiving Privacy only as a negative barrier and not as a positive factor motivating adoption. In this sense, since “*adoption begins only after the initial consumers resistance is overcome*” (Ram, 1987, p.208) it is necessary to continue to investigate the reasons that lead individuals to erect such barriers, considering resistance factors as a separate category, autonomous and independent from that of adoption factors, not assuming a priori their correspondence and polarization.

In conclusion, the present study continues the “literature of resistance”, adding two important contributions: on the one hand, the macro-categorization gives relevance to the peculiar characteristics of smart objects, which create new adoption drivers compared to traditional ones; on the other hand, the achieved results highlight the importance of analysing resistance barriers and positive factors for adoption as independent, autonomous and not necessarily polarized and correspondent categories.

Appendix

Table 1

city	incident	pdct_srvc	when	reasons
Per favore, inserisci il tuo CITY name.	Per favore, pensa e descrivi una recente occasione in cui hai avuto la possibilità di acquistare un prodotto con AI incorporata e/o di utilizzare un servizio con AI incorporata ma non lo hai acquistato/utilizzato (minimo 500 caratteri)	Di quale prodotto o servizio si trattava?	Quando è accaduto l'episodio?	Quali sono le ragioni che ti hanno portato a non acquistare il prodotto o utilizzare il servizio?

thinkfeel	numberprodct	typeprdct	numberserv	typeser	gender
Esattamente, cosa hai provato e pensato durante l'episodio?	Quanti device con AI incorporata possiedi?	Quale tipo di device con AI incorporata possiedi?	Quanti servizi con AI incorporata utilizzi?	Quale tipo di servizi con AI incorporata utilizzi?	Genere

Table 2

city	incident	pdct_srvc	when	reasons
Per favore, inserisci il tuo CITY name.	Per favore, pensa e descrivi una recente occasione in cui hai avuto, e colto, la possibilità di acquistare un prodotto con AI incorporata e/o di utilizzare un servizio con AI incorporata.(minimo 500 caratteri)	Di quale prodotto o servizio si trattava?	Quando è accaduto l'episodio?	Quali sono le ragioni che ti hanno portato ad acquistare il prodotto o utilizzare il servizio?

thinkfeel	numberprodct	typeprdct	numberserv	typeser	gender
Esattamente, cosa hai provato e pensato durante l'episodio?	Quanti device con AI incorporata possiedi?	Quale tipo di device con AI incorporata possiedi?	Quanti servizi con AI incorporata utilizzi?	Quale tipo di servizi con AI incorporata utilizzi?	Genere

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Department of Impresa and Management

Chair of Consumer Behavior

Consumers and IoT: a qualitative analysis of factors pro and against the smart objects' adoption

SUMMARY

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ACADEMIC YEAR 2019-2020

Introduction

The digitalization of the physical world occurred with the advent of the Internet of Things (IoT), has consecrated the entrance of human beings into the "fourth industrial revolution". Indeed, the IoT allows the connection to the Internet of physical objects equipped with sensors, which thus become "smart" and anthropomorphised, able to listen, communicate, capture and transmit information to the outside world. The relationship between humans and objects has therefore changed compared to the one with traditional objects, as individuals no longer relate to passive entities, but interact with active and autonomous devices.

The benefits and advantages provided by IoT have increased its ubiquity across many different sectors, so that today we can observe its applications in various field such as human health and productivity, automotive, homes, factories, shops, cities and in the daily life of individuals.

The enormous impact of IoT and its ability to create value for the stakeholders involved, has always permitted positive predictions about its growth by scholars. These forecasts, however, have found evident limits and difficulties in their occurrence: if in 2015 Ibm estimated 1 trillion connected devices in 2020, the reality of the facts recorded 18.4 billion in 2018, and the expectations for 2023 are oriented on decisively lower numbers (29.3 billion). Although the growth of IoT is positive over the years, the objects connected remains inferior to the previous estimates, and the failure rate of innovative products remains high. One of the main causes of the slowdown in the Innovations adoption is the consumers resistance to smart devices, which is the main topic of this study.

In light of this, the previous literature has investigated the adoption of Innovations mainly in a positive way, focusing exclusively on the drivers that positively influence the evaluation of a new product, assuming that the negative factors were the exact opposites and specular of the positive ones ("Complementary Assumption", Sutton). From this emerges the need to analyse the barriers of resistance implemented by the consumer as a category in itself, independent by the positive factors of adoption of smart objects, in order to verify the relationship and the possible correspondence between these two.

Therefore, the present research focuses on the role of the consumer, analysing the positive and negative drivers that influence the process of adoption of AI devices. The categorization of positive and negative factors will be carried out with a qualitative method through the use of the Critical Incident Technique.

The study of the relationship of these drivers has led to relevant conclusions: firstly, more than half of respondents have given reasons for adoption that totally differ from those for rejection, confirming that the reasons pro adoption are not necessarily the exact opposite of those against; secondly, results proved the existence of factors of adoption (resistance) to these devices that are not polarized, i.e. that act only unidirectionally, not presenting their negative (positive) opposite. In other words, it emerges that the reason why individuals decide to reject a smart device is not always the exact opposite of the reason that drives them to adopt it: for example, "Privacy" drives only negatively the adoption, since there is no positive specular factor that leads consumers to perceive "protection" of their personal data.

In Chapter I the economic and technical overview of the Internet of Things will be presented, with the aim of introducing the phenomenon and highlighting both its potential value and limitations.

In Chapter II the analysis of the previous literature on the diffusion and adoption of innovative products will be conducted. The main models will be investigated, highlighting the major drivers of adoption and resistance already identified by scholars.
In conclusion, Chapter III will be dedicated to data analysis: after an overview of the qualitative method and the Critical Incident Technique, the adoption and resistance categories and the relationships between them will be described and commented.

Chapter I

IoT and Smart Objects: the New Frontier

In this Chapter, a technical and economic overview of the Internet of Things will be conducted in order to introduce the topic of my analysis.

IoT and Smart Objects: Technical and Economical Overview

The expression "Internet of Things" was coined for the first time in 1999 by Kevin Ashton who during a presentation at P&G introduced the possibility of connecting to the Internet any object with sensors.
IoT is a digital transformation that leads us towards the so-called Industry 4.0, defined as the "fourth industrial revolution". IoT has significantly changed the way individuals used to conceive traditional objects: thanks to a network connectivity objects are now able to collect, analyse and transmit data detected from the environment, communicating with each other and working as a whole assembly-line.
Technically, smart objects are equipped with (Vasseur, 2010): a sensor in order to sense external physical factors; a tiny microprocessor which allows to transform the data captured, providing the device with the necessary computational power to be "smart"; a communication device able to send data to the outside world and receive input from other devices; and a power source which provides the electrical energy.
Smart objects are considered a disruptive innovation because of their peculiar features that allow users to perceive a significant novelty and difference compared to traditional objects. An object is defined "smart" to the extent of its ability to exercise: agency, i.e. the capacity to affect and be affected by other entities (Franklin et al., 1996); autonomy, i.e. the ability to function independently (Parasuraman et al., 2000); and authority, namely the capacity to control other entities and make decisions for them (Hansen et al., 2007). The degree of these three properties in a specific object determines how effectively "smart" it is: on the one hand, there are objects with a low degree of smartness that require human intervention at various points for an action to succeed; on the other, devices with a high level of autonomy are able to execute actions independently, without human intervention (Parasuraman et al., 2000).
More deeply, among the various characteristics that render smart objects innovative, there are certainly "intelligence", "ubiquity" and "connectivity" (Mani et al., 2016), which allow devices to: exchange information with the external environment through communication protocols; act independently basing their actions on data previously captured by sensors; be connected to other objects and devices, so that they can be used by consumers without limits of place and time. Moreover, a key feature that derives from the high

degree of Connectivity and Autonomy of smart objects is the "Interoperability", defined as "*the degree to which two products or programs can be used together, or the quality of being able to be used together*" (Cambridge Dictionary). Interoperability has been recognised by McKinsey as a significant variable in the value creation of IoT, reporting that 40% of the total potential value generated can be unlocked only if numerous IoT devices work together. In numbers, Interoperability allows IoT technology to have an impact of more than $4 trillion per year in 2025.

The advent of IoT has enabled traditional objects to become increasingly like human beings, thanks to their high degree of anthropomorphization: due to their ability to communicate, listen, transmit and process data, they embody something more than passive entities that consumers invest with meaning (Belk, 1988). As a direct consequence, the user-device relationship has therefore changed compared to the one with traditional objects, as individuals no longer relate to passive entities, but interact with active and autonomous devices.

IoT Market Analysis and Growth Prospective

The rapid growth of IoT over the years allows to make positive predictions about its future evolution: the global IoT market was valued at US$ 190.0 Bn in 2010 and it is projected to reach US$ 1,102.6 Bn by 2026, exhibiting a CAGR of 24.7% in the forecast period (Fortune Business Insight, 2019). The strong market performance is due to the fact that smart objects have become an inevitable part of people's daily lives, and this is demonstrated by IoTs adoption rate, which is positive for both businesses and consumers: globally, 127 new devices connected to the Internet are estimated every second (Petel et al., 2017), and the total number of objects connected worldwide is expected to rise to 75.44 billion by 2025, about five times the connected devices in 2015 (Statista Research Department, 2016).

Various factors contribute to the positive sign of growth in the IoT market. First of all, over the last years many resources have been allocated in order to improve the infrastructures that enhance connectivity between devices located in different areas. As evidence of the growth, McKinsey has estimated that investments in IoT technology are projected to rise 13.6 % per year through 2022. Moreover, connectivity is expected to benefit from the introduction of the 5G network, which will have an improved performance due to the increased bandwidth, allowing new IoT applications such as Virtual and Augmented Reality. Secondly, the general technological progress occurred in recent years is an important growth factor: as far as IoT is concerned, technological progress has led to a sophistication of devices (that are now functioning better and with a lower power requirement) and a decrease in the associated production costs. Consequently, the so-called "easy-to-use" devices have been developed, i.e. smart objects with a lower price and easier to use, in order to ensure that individuals are not prevented from adopting them because of their complexity. Finally, a further growth factor for IoT is the potential of already existing traditional IT devices. Although they have a moderate growth rate (2% per year), these devices cover a significant market share (more than 5 billion smartphones, 2 billion PC, and 1 billion tablets in the world). The possibility of connecting such a multitude of already existing devices (for which there is no need to sustain any production cost) to IoT is a great opportunity that fosters the growth of the entire industry (Dahlqvist et al., 2019).

Application Fields and Stakeholders

The numerous benefits provided by smart objects and their ubiquitous connectivity have enabled the application of IoT in many different fields. First of all, the ability of smart devices to capture information from the external environment and transmit it to other devices, renders them an important source of "Big Data", i.e. data that individually have no value, but analysed in large volumes by Artificial Intelligence systems allow to extract patterns and strategic insights about consumers, necessary for business decisions. In addition to the benefits for companies, the advantages provided by IoT have increased its applications across many different sectors, among which:

- Humans: IoT applications in health field enabled a better monitoring of individuals' medical parameters and a more efficient management of emergency cases, with a consequent reduction of unnecessary medical visits and of the costs of assistance. In general, the application of IoT to this sector could have an economic impact of $170 billion to $1.6 trillion per year in 2025 and could enable benefits for society worth more than $500 billion per year.
- Home: an increasing number of devices are replacing humans in household tasks, consequently reducing their workload. In addition to smart home appliances, an important role has been assumed by voice assistants, i.e. AI-based operators able to recognise human language, receive orders and perform actions. The reason why smart assistants have so much hit the market is the implementation of the "voice recognition" through which individuals are able to connect to the Internet with the sole use of their voice, without any keyboard, screen or mouse (Oreskovic, 2020). McKinsey estimated that IoT applications in the home could have a total economic impact of $200 to $350 billion per year in 2025.
- Cities: smart devices are used to collect and analyse data in order to increase efficiency by improving public utilities, infrastructures. Authorities are encouraging to invest in smart cities: UE has allocated 456.6 billion euros in funds related to smart applications in towns (Ansa, 2019). Overall, is estimated that IoT applications in cities could have an impact of $930 billion to $1.6 trillion per year in 2025.
- Factories: IoT devices are used in factories in order to optimise the production process, monitor machines, and collect useful data to improve logistics. In this field, IoT could potentially generate an economic impact of $1.2 trillion to $3.7 trillion per year.
- Vehicles: the automotive industry has adopted smart objects in order to monitor the manufacturing process and report real time data about every part of the vehicle (such as tyre pressure, location of other vehicles etc.). Moreover, the connected cars category has emerged thanks to IoT, which are either self-driven or driver assisted vehicles, that fall within the field of automation. In general, it is estimated that IoT technology in this field could generate $210 billion to $740 billion per year by 2025.
- The outside environment: IoT is implemented with the aim of increasing safety and security (by detecting phenomena such as pollution, earthquakes, fires, etc.) and advancing navigation systems (by improving the routing of ships, airplanes etc.). The economic impact of IoT in this industry is expected to be about of $560 to $850 billion per year in 2025.

Numerous stakeholders are affected by the Innovation of IoT, and relevant implications need to be considered, as smart objects create both opportunities and risks for the actors involved.
Above all, those who are directly and indirectly impacted by IoT are consumers: McKinsey estimates that users could capture about 90% of the value generated by IoT appliances. For instance, the increased competition in IoT market has had positive consequences for consumers: companies are offering products of a higher quality, with better features at a lower cost. The other side of the coin are the associated risks to individuals' privacy since smart objects, by definition, collect information and real time data from their surroundings and transmit them to other entities. The first problem is that individuals often do not have control over the nature and amount of data captured by such devices; the second issue is the lack of control over the transmission of such data to third parties, thereby risking to disclose sensitive and personal information to undesirable subjects. In addition, the increase number of interconnected devices – thanks to interoperability – creates more entry points for hackers and leaves sensitive information vulnerable.
The second stakeholder are firms that have invested in IoT in order to modernise their offer. The major problem for these companies, even if their purpose is to get insights about consumers, they often have a large amount of data but no ability to correctly analyse them. In fact, generally IoT technologies are not fully exploited by businesses which mostly analyse data to detect anomalies through the workflows, rather than using them for marketing purposes such as consumers' behaviour prediction and personalisation of the offer.
To conclude, the advent of IoT has radically impacted retailers: the most impactful change is the increase in touchpoints between brand and consumer, transforming their relationship from linear to multi-interface. The introduction of mobile shopping, for instance, allows consumers to buy anything at anytime from anywhere, leading to a different shopping experience.

Limitations to Adoption

The potential of IoT and smart objects has always made scholars forecast very positively, since in 2015 Ibm predicted a trillion connected devices in 2020. Nevertheless, the positivity of these numbers has not been fulfilled, so much so that forecast lowered to 28 billion connected devices by 2021. CISCO reported that in 2018 users in the world connected to the Internet were 18.4 billion, and these have been predicted to rise to 29.3 billion by 2023. Accordingly, by 2023 two thirds of the global population will have an Internet connection, with a total of 5.3 billion internet users (66% of the world population) compared to 3.9 billion Internet users in 2018. Even though the growth of IoT phenomenon is still positive through the years, the registered numbers of devices connected to the Internet are lower than the initial forecasts, which were too optimistic. The reasons for this discrepancy are multiple. First of all, the very nature of Innovations involves a certain degree of risk: it is not uncommon to find on the market the so-called "slow-diffusing innovations", i.e. innovations slowly adopted by consumers despite the obvious competitive advantage over existing products, such as the dishwasher, the microwave oven, the alternative fuel vehicles and so on(Garcia et al., 2007). Slow-diffusing innovations have negative repercussions on the firms because, in addition to creating

delays in ROI, they can cause negative paybacks if the product is removed from the market before sales take off. Therefore, it is necessary to understand why Innovations are not immediately accepted by consumers. Secondly, the failure of some innovations can be attributed to evident reasons, such as high market prices in the launch phase, low quality of the product, low competitiveness, lack of innovation etc.
Besides the reasons mentioned, one of the primary causes of innovation failure is the so-called “consumer resistance”: individuals reject innovative products when these are in conflict with their habits, beliefs, attitudes, traditions and values, forcing them to significantly change their status quo.
Hence, the focus of my research will be on the role of consumers, and on how they tend to approach the world of IoT and smart objects. This analysis has the aim to identify the main critical incidents driving individuals to adopt or reject smart devices, as well as trying to respond to the discrepancy between the great potential of IoT Innovation and its effective use by consumers.

Chapter II

Main Drivers of Adoption and Barriers of Resistance in Previous Literature

The purpose of this Chapter is to provide an accurate overview of the previous literature dealing with the diffusion of technological products, maintaining the focus on critical incidents which affect consumers’ adoption of smart objects.

Literature on Adoption

In this section the main models which have mostly focused on adoption factors will be analysed, considering the fundamental characteristics and empirical findings related to smart objects.
Rogers (1962) defined diffusion as the conveyance of a new idea among people, highlighting the centrality of novelty, communication and social system on which his model is founded.
In the Diffusion of Innovation (DOI) theory, Rogers identified five essential factors which directly impact the consumers’ decision-making process to adopt an innovation:

- “Relative Advantage” is the degree to which an innovation is perceived as better than the idea it supersedes, leading individuals to abandon their status quo and adopting the new product;
- “Compatibility” is the degree to which an innovation is perceived as being consistent with the existing values, past experiences, and needs of potential adopters;
- “Trialability” is the degree to which an innovation may be experimented on a limited basis before deciding to adopt it definitively;
- “Observability” is the degree to which the results of an innovation are visible to others. The more observable the results of innovation are, the more likely it is to be adopted;
- “Complexity” is the degree to which an innovation is perceived difficult to understand and use.

On the basis of DOI, two further constructs have been elaborated by Moore and Benbasat (1991):

- “Image” is the degree to which use of an innovation is perceived to enhance one's social status;
- “Voluntariness of use” is the degree to which use of the innovation is perceived as voluntary.

Moreover, the authors explained the difference between primary and secondary attributes: the former are the objective characteristics of the innovation; the latter indicate the attribute perception of the potential adopter. Since the same primary attribute can be perceived differently by each individual, the "perception *of using* the innovation" is the key variable for the analysis of innovation diffusion rather than the "perception *of the innovation* itself".

According to Theory of Reasoned Action (Fishbein and Ajzen, 1975), human behaviour directly derives from information and beliefs formed on that particular behaviour, namely:

- "Attitude toward behaviour", i.e. the evaluation of the consequences which the behaviour leads to.
- "Subjective norm", i.e. the opinion that people important to the individual have regarding that behaviour.

As general rule, the more attitude towards behaviour and subjective norms are strong and positive, the more the individual will be motivated to implement the behaviour.

Since TRA considers intention as a good predictor of behaviour only in cases in which individuals have full control over their behavioural performance, the Theory of Planned Behaviour (TPB) has been developed (Ajzen, 1991). TPB maintained the focus on the intention of implementing a certain behaviour, which incorporates individuals' motivational facts: the stronger the intention, the more likely the behaviour will be performed. What makes the TPB different from the TRA is the concept of "Perceived Behavioural Control", which indicates people's perception of the degree of easiness or difficulty in performing a behaviour. According to Ajzen, considering an equal intention of behave, a greater Perceived Behavioural Control increases the individual's effort to successfully perform the behaviour in question. In light of this, the "Self-Efficacy" driver has been elaborated in order to indicate the judgement individuals have about their ability to use a technology.

In 1989 Davis has revisited TRA by considering the specific technological sector and developed The Theory of Acceptance Model (TAM). Accordingly, the individual adoption system is influenced by "Perceived Usefulness" (PU) and "Perceived Ease of Use" (PEOU): the former is the belief that the use of the innovative product improves individual's performance; the latter concerns the fact that the use of the product is easy and effortless. Moreover, the more a product is perceived as easy to use, the more it will increase the usefulness in the work context. Further research confirmed PU and PEOU as positive determinants of attitude, even though in different ways: the former has a greater impact than the latter, confirming that "*no amount of PEOU will compensate for low Usefulness of a product*".

Venkatesh et al. (2003) developed the User Acceptance of Information Technology (UTAUT) theory, with the aim of systematising the existing models and theoretical contributions in the field of technology acceptance so far. The authors found three determinants directed to the "Intention" to use technology: "Performance Expectancy" (the performance consequences of using a technology), "Effort Expectancy" (the degree of ease perceived in using a specific technology), and "Social Influence". Moreover, in addition to the Intention, "Usage behaviour" is impacted by "Facilitating Conditions" (users belief that exist an organizational infrastructure which support the use of the innovative system).

With the aim of extending the UTAT model from the organizational context to the specific consumer setting, UTAT2 (Venkatesh et al., 2012) has been developed, which incorporates three new constructs, namely "Hedonic motivation", "Perceived Price" and "Experience and Habits.

Criticisms and Limitations

Despite being widely used as a lens for many on the diffusion field, the described models have been considerably criticised.

Basically, literature on adoption have been focusing on reasons for performing a certain behaviour (positive factors) rather than *not* performing it (rejection factors), assuming that the reasons for the latter were the exact opposites of the former (Complementary Assumption, Sutton 2004).

Contrary to evidences which demonstrate the economic potential of innovations, data shows that innovations still tend to fail, since 95% of innovative products and 92% of startups do not achieve success. In light of this, it is important not to limit the analysis to the factors that positively influence the adoption, and to extend it also to negative drivers leading consumers to rejection. Hence, it is necessary to consider the non-logical, a-priori correspondence between factors for and against the adoption of an innovation.

Literature on Resistance

One of the major reasons of the still high failure rate of innovative products is the resistance implemented by consumers (Ram and Shets, 1989).

Based on the concept of resistance as a natural reaction of human beings to changes from their status quo, Ram (1987) developed Model of Innovation Resistance in order to comprehend and overcome barriers to adoption. The model analyses the impact on innovation resistance considering "Perceived Innovation Characteristics", "Consumers Characteristics" and "Characteristics of Propagation Mechanisms" as three separate categories. The key point of Ram model lies in understanding the factors of consumer resistance to Innovation, in order to be able to modify the Innovation itself and enable individuals to adopt it more easily.

In 1989 Ram and Shets's developed a theoretical framework in which two main barriers of innovation resistance have been identified, namely the functional and psychological ones.

Functional barriers include resistance factors closely related to characteristics of the innovative product. Basically, these refer to the usage barriers ("*the degree to which an innovation is perceived as requiring changes in consumers' routines*"), the value barriers (the perception of the innovation price-performance ratio) and the risk barriers ("*the degree of uncertainty in regard to financial, functional and social consequences of using an innovation*") of innovation.

Psychological barriers are divided into tradition and norm barriers (which occur when innovation creates a disruption in the daily routine of the individual), and image barriers (the perception of the unfavorability and incompatibility of the innovative product image).

Even though Ram and Shets (1989) have extensively contributed to the literature on resistance their model in the present day leads to the identification of some objective limits. First of all, considering the technological

and digital innovations of the last 30 years, the model seems anachronistic and incomplete as it does not consider essential elements of digitisation. In light of this, it is necessary to consider in the analysis of barriers the characteristics of smart devices that differentiate them from traditional objects, i.e. Intelligence, Connectivity and Ubiquity. As already discussed in Chapter I, these characteristics lead to important problems of privacy and intrusiveness, therefore it is necessary to consider them in the analysis.
Secondly, the model is limited to analysing the situational antecedents of resistance - functional and psychological barriers - without considering the personal predispositions of the individual (such as inertia, which is the lowest level of resistance according to which individuals are simply passive and feel disinclined to adopt) and demographic characteristics (in particular age).
In 1991 Bagozzi et al. developed "Consumer resistance to, and acceptance of, innovation" model in which decision-making process is analysed when consuders have to choose to adopt an innovation in relation to their individual well-being.

Research Question

In the light of the economic overview, a slowdown in the growth of smart device adoption has emerged, despite their potential positive benefits. As analysed in Chapter II, the previous literature focused mainly on the analysis of the positive factors that lead to the adoption of innovations, arguing that it is not necessary to investigate the negative drivers, as these are the exact negative counterparts to those of adoption.
In light of these considerations, it is necessary to understand the reasons that lead consumers to create the barriers of resistance to the adoption of Artificial Intelligence objects. The aim of my research is to identify the categories of adoption and resistance to smart objects by consumers, considering these two as separate clusters of factors, not assuming their a-priori correspondence and polarization. Therefore, the analysis will focus on the investigation of the relationship between positive and negative adoption factors, verifying whether or not these are unilateral drivers, i.e. drivers that act on adoption only positively or negatively.

Chapter III

Qualitative Analysis and Categorization of Factors Pro and Against Adoption

In this Chapter the data analysis will be carried out in order to answer the research question elaborated at the end of Chapter II.

Research Methodology

The decision to use the qualitative method derives from the exploratory approach required by the research question. Specifically, the very purpose of my research is purely qualitative, since it aims to investigate the mental processes of consumers and the factors that affect the choice to adopt or reject a smart object. The qualitative method is widely used when is necessary to understand certain aspects of personal experiences and perceptions of individuals in order to determine their attitudes towards a particular behaviour. The main reason why I chose to adopt this methodology is that it provides great freedom to the respondent to express

themselves without limiting their answers to questionnaires and closed questions: it reveals details, opinions, points of view and perspectives, suggesting new directions of analysis that would otherwise remain hidden. The qualitative method can therefore be defined as “holistic”, since it does not stop at a numerical analysis of “how much” a phenomenon is relevant, but it allows researchers to respond accurately questions about “how” and “why” it happens, also considering the social, cultural, personal aspects.
The tool used for the analysis is the Critical Incident Technique (CIT): introduced in 1954, it is an exploratory approach used by researchers with the aim of capturing factual stories or episodes about a given experience. CIT consists of a set of formalised procedures to collect observations on a specific human behaviour, with the aim of creating a respondent classification system that provides relevant insights to solve a practical problem. It is a classification technique based on inductive grouping procedures, belonging to the same family of quantitative methods such as factory and cluster analysis. It is based on the content analysis of the experiences reported by the interviewees through “coding”, which is the activity of “*discerning small elements in data that can retain meaning if lifted out of context*” (Ely et al., 1997).
Validity and reliability of CIT has been demonstrated by many scholars (Andersson et al., 1964; Ronan et al., 1974; White et al., 1981) who have proved that it is effective in generating a comprehensive and detailed description of a specific content domain.
More deeply, CIT analyses the responses by focusing on *incidents* – observable human activities complete enough to make deductions about the person performing them (Bitner et al., 1990) - that are *critical* from the respondent’s perspective - i.e. that have actually and significantly impacted the final outcome both positively and negatively - considering their background (Woolsey, 1986).

Analysis

In order to gather the information needed, the tool used was the open questionnaire, submitted online to 61 respondents: it is a sample of convenience, composed of students attending university, between 22 and 24 years old. The demographic analysis reported the presence of 26 men and 35 women in the sample.
The respondents were submitted two online questionnaires in which the same questions were asked in both a negative and a positive scenario. The decision to submit two surveys lies in the benefits of comparing two opposite scenarios of the same person: in this way both positive and negative consumers’ points of view on the same issue are analysed. The positive scenario indicates the factors of adoption, while the negative one represents the resistance drivers to smart objects: categories of adoption and resistance can be formed, and their possible relationships and correspondences can be investigated.

Results

First of all, the results show a greater use of AI services compared to AI physical products due to the intangible nature of AI services that leads individuals to make use of these algorithms without being fully aware of them. The services and products emerged have been divided into ten categories according to their

nature and use: findings show that the most widely used devices are Voice Assistants, followed by Streaming Online services, Smart Watches and all the others.
The questionnaires analysis revealed a branched categorization of the factors: the two main macro-categories ("individual characteristics" and "smart object characteristics") contain various sub-categories, which in turn are impacted by positive and negative adoption drivers. In accordance with Ram (1987) the distinction between "individual characteristics" and "smart objects' characteristics" has been confirmed. This categorization adds to the previous literature the distinctiveness of smart devices' features compared to traditional objects, i.e. Autonomy, Connectivity and Ubiquity: it was found that these characteristics are not neutral for consumers, instead they create new positive and negative drivers for adoption.
Comparing the results for these two macro categories, it emerged that "individual characteristics" have a significantly greater impact on consumers' adoption process compared to "smart object characteristics". In general, at a macro level the polarization is almost perfect, since the magnitude of adoption drivers and resistance barriers is approximately equal in both categories.
According to the analysis of the macro-categories, it emerges the impact of 13 positive factors on the adoption of smart objects: each of them presents the corresponding negative driver that acts symmetrically on the resistance to these devices. However, it is not possible to generalize that each positive adoption driver has its negative opposite pole of resistance, as significant results regarding the non-speculiarity of adoption drivers have been achieved through the comparative analysis of the positive adoption scenario and the negative one experienced by the same individual: out of 61 respondents, more than half motivated the rejection of these objects with different and not symmetrical factors to those given for the adoption. Moreover, three factors have been identified that impact the adoption process unidirectionally, thus not presenting the opposite counterpart. The well-established belief in literature that it is sufficient to analyse just the positive factors of adoption since the resistance ones are merely the opposites, has therefore been contested by results, pointing out the need to better comprehend the barriers of resistance as well as the drivers of adoption. Specifically, on the one hand, the results reveal the "Visibility" and "Social Status" factors, belonging to the "individual characteristics" macro-category, which only have a positive impact on the adoption of smart objects, since no one have perceived these drivers as resistance barriers; on the other hand, it emerged that the "Privacy Issues" (belonging to the "smart objects' characteristics") act solely as a deterrent to the adoption of smart devices, since no category representing its positive counterpart has been identified. Hence, no positive factor has emerged that would make consumers perceive protection and security in the processing of their personal data.
Confirming the strong consumers resistance to adoption, the sub-category of "Psychological Traits" emerged among the "individual characteristics". Two predominant psychological profiles have been identified: the "Innovativeness" are individuals who are passionate about technological innovations and are naturally inclined to adoption; the "Sceptics" are users who are distrustful of innovation and novelty in general. The significant majority of Sceptics compared to Innovators is a sign that consumers have still difficulty in completely comprehending the value of AI products, confirming the existence of strong diffidence and

individual barriers to the adoption of smart objects. This evidence confirms the importance of studying and comprehending the negative factors that form such barriers, in addition to those of adoption.

Managerial Implications and Research Limitations

The benefits brought by IoT devices are not always comprehended and accepted by consumers, who are sceptical and erect barriers of resistance. In order for IoT to effectively grow and deliver its benefits to the various stakeholders, these barriers of resistance need to be removed.

At a managerial level it is increasingly necessary to implement strategies to destroy these barriers of resistance by making individuals understand the real potential of these devices.

Moreover, the results obtained about the unnecessary correspondence between positive and negative adoption factors suggest that scholars should continue to study the nature of the barriers, analysing them as distinct and separate category from the positive adoption factors.

In addition, the two macro categories identified ("individual characteristics" and "smart object characteristics") highlight the unique attributes of smart devices that differentiate them from traditional objects: the importance of considering these characteristics in the analysis lies in the fact that these are not neutral for consumers, instead they form new positive and negative drivers of adoption. Specifically, the "privacy" factor assumed particular importance, which is a new negative driver for adoption that did not exist in the context of traditional objects. Furthermore, since it has emerged that privacy is a driver that only acts unidirectionally, i.e. only negatively, it is possible to use this result to continue investigating the nature of this barrier.

In terms of future research, the present study provides a further insight into the field of analysis of resistance barriers, providing relevance to the factors that contribute to their formation, considering them independently from the positive drivers of adoption.

Nonetheless, the present study has some limitations: firstly, the analysed dataset represents a small sample of the total population, so the same research question can be investigated across a larger and more representative sample; secondly, the decision to use CIT analysis derives from the exploratory stag of research, so future research that would implement a quantitative approach will be useful to determine the magnitude of the barriers of resistance and adoption factors and their correlations.

Furthermore, the results obtained on the "demographic variable" highlight the different approach to innovation according to age: as the survey did not ask the age of respondents, further research could investigate the relationship between age and resistance barriers, identifying the different barriers erected by different age groups.

Conclusions

The importance of IoT in many fields and the benefits brought by this innovation for many stakeholders, have made scholars focus on predicting its future growth, forecasting hyper-positive predictions about the spread of objects connected to the Internet in the coming years. Although the growth of IoT continues to be positive, it has encountered difficulties that have not allowed it to record the expected numbers.

In order to understand the reason for the "slow-diffusion" of smart objects among consumers, the main models of adoption and resistance to innovative products have been analysed in Chapter II. The major topic that emerged, is that the previous literature has mainly focused on research and analysis only of positive adoption factors, based on the so-called "Complementary Assumption" (Sutton, 2004): the latter assumes that, since the reasons why consumers *do not* buy an innovative product are the exact opposite and speculative reasons for adoption, it is sufficient to analyse exclusively the positive drivers.

With the aim of identifying the positive adoption factors and the barriers of resistance to smart objects, and of verifying whether or not there is specularity between these two, it was necessary to consider negative drivers as a category by itself, not dependent or a-priori opposed to the one of positive drivers.

The achieved categorization provides the distinction between two macro-categories of factors: on the one hand, the "individual characteristics"; on the other, "smart object characteristics", i.e. the new features typical of smart devices (Autonomy, Intelligence, Ubiquity) that make the individual vulnerable to this technology. The main contribution of this categorization to the previous literature (which already distinguished between "individual characteristics" and "product characteristics") is to highlight the revolutionary attributes of smart objects compared to traditional ones, capable of creating new adoption and rejection drivers that did not exist before. These two macro categories in turn contain both positive and negative factors of adoption, among which the relationships have been studied.

The results obtained from the analysis are in contrast with Sutton's Complementary Assumption, rejecting the a-priori correspondence of the positive and negative adoption categories, for two main reasons: firstly, through the comparative analysis of a positive and a negative adoption scenario of the same individual, out of 61 respondents more than half have given reasons for adoption that totally differ from those for rejection. Secondly, three factors were identified that act unidirectionally on adoption, of which two impact only positively (Visibility and Social Status), and one only negatively (Privacy Issues). This means that no respondents reported to perceive the Visibility of the smart object as a barrier to adoption, nor to perceive a lowering of their social role due to the adoption of such devices; similarly, no "protection and confidentiality" factor in the processing of their personal data was recorded, thus perceiving Privacy only as a negative barrier and not as a positive factor motivating adoption.

In conclusion, the present study continues the "literature of resistance", adding two important contributions: on the one hand, the macro-categorization gives relevance to the peculiar characteristics of smart objects, which create new adoption drivers compared to traditional ones; on the other hand, the achieved results help to highlight the importance of analysing resistance barriers and positive factors for adoption as independent, autonomous and not necessarily polarized and correspondent categories.