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Master Thesis

Artificial Intelligence as General Purpose Technology: An Empirical and Applied Analysis of its Perception

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Bender, I don't care whether you have money.
I love you for your artificial intelligence and your sincerity simulator.
FUTURAMA (1999, S1-E10). "A FLIGHT TO REMEMBER".

Summary

Intelligence is understood as the ability of an agent to successfully face and solve new or unknown situations and problems and in the case of humans and animals, intelligence also seems to be identifiable as the complex of all those faculties of a cognitive type or emotional that contribute or would contribute to this capacity. In computer science, however, it is understood in the form of artificiality and means the development of hardware and software systems endowed with capabilities typical of the human being that autonomously pursue a defined purpose by making decisions that, up to that moment, were usually entrusted to human beings.

This concept may have a science fiction nature, but the reality of the facts is that many everyday objects are already or are about to become intelligent in order to best meet our needs by creating a great technological and social leap.

This would radically transform the perception towards everyday products and given that the public shapes the demand for technology, obtaining acceptance from end users will be fundamental for the large-scale diffusion of Artificial Intelligence (AI) products based.

A Technology Acceptance Model (TAM) research model with a measurement scale of 21 elements was created to assess the consumer's intention to use an autonomous vehicle in the not too distant future. The model was validated through a Structural Equation Modeling (SEM) analysis that was performed on 564 responses collected from an online survey specifically designed for this purpose. The results obtained validated a large part of the TAM model, however, leaving room for some interpretations on future prospects and on aspects to be taken into consideration for subsequent developments and implementations of AI based products.

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Introduction

In the common imagination, Artificial Intelligence (AI) is represented by androids and robots that have the ability to behave, think and act like human beings, sometimes even to feel emotions.
Artificial Intelligence is defined as a set of studies and techniques, typical of computer science but with significant philosophical and social implications, which has as its purpose the creation of programs and technological systems capable of solving problems and performing tasks normally attributable to the mind and to human capabilities.
Artificial Intelligence, despite its generic perception, is not just robotics. Numerous systems fall into this category (virtual assistants, self-driving cars, smartwatches, etc.), because they are able to interface with the inputs with which they are tested, creating expected or unexpected outputs and given recent progress. It is possible to identify Artificial Intelligence as the discipline that deals with creating machines (hardware and software) capable of operating autonomously.
Of course, these are still limited systems, designed to fulfil specific tasks but the current rapid technological developments have allowed significant increases in capabilities, hoping for a fast and dizzying diffusion of this technology. It follows that Artificial Intelligence, therefore, is a container term that includes different fields, purposes, tasks and characteristics. The combination of these factors gives rise to more or less advanced applications.
This document will shed light on the different aspects of Artificial Intelligence and consists of two main parts. The first part is of a theoretical nature and analysis of the state of the art of Artificial Intelligence and consists of the first and second chapter.
In the first chapter, the work will focus on the analysis of General Purpose Technologies (GPTs), which are technologies that throughout history have made changes to the entire economy and therefore have the potential to implement drastic changes on society with an impact on pre-existing economic and social structures. Among these technologies, the most recent would seem to be Artificial Intelligence which, although in a primordial state, is configured to be able to adhere to this type of classification.

In the second chapter, Artificial Intelligence will be evaluated as a whole, from the historical point of view, from its definition, from its technical functioning and from the potential benefits and/or disadvantages it could bring, all with a view to analysing the product as GPT from the point of view of literature and through the presentations of some concrete and commonly used applications.
The advent of Artificial Intelligence, also from a General Purpose Technology perspective, could have truly transformative effects, but future acceptance and future use are still uncertain so it is likely that both technological progress and consumer demand will determine the pace and the extent of market development. In this regard, the second part of the paper is dedicated to a prospective analysis of the consumer whose main purpose is to develop and empirically test a research model that helps explain the acceptance of AI by consumers. In this case, the Technology Acceptance Model (TAM) was used to evaluate both the effects of perceived utility and perceived ease of use on people's attitudes and behavioural intentions to use a product equipped with Artificial Intelligence. In pragmatic terms, the statistical analysis of quantitative data (collected through an online survey) is discussed and examined using Structural Equation Modeling (SEM).
The third chapter consists of a section dedicated to deepening the theoretical framework of the TAM adopted in this analysis and its historical and literary foundations in evaluating the importance of acceptance by the consumer. Continuing, the research methodology and demographic statistics will be illustrated, and then, subsequently, the results and the relative conclusions will be analysed.

Chapter 1

General Purpose Technologies

1.1 Definition

In literature, technology is not always clearly defined, but in order to give a definition, it could be said that technological knowledge, known as technology, is the set of ideas that specifies all the activities that create economic value. It is incorporated into capital goods, human capital, organizational forms and institutions (Lipsey, Carlaw & Bekar, 2005).
Analysing this definition, it is possible to perceive how technology is separated from pure science on the one hand, and its personification in capital goods and the economic structure on the other. In fact, the standard abbreviation is used to refer to products as technologies and therefore the reference is strictly addressed to the knowledge of how to make and use these products (Bekar, Carlaw & Lipsey, 2018).
The technologies are not all the same, within the economy it is possible to represent on one hand incremental technologies, which allow production systems to develop gradually, on the other, those with a revolutionary impact, which impose a new structure of dependencies and complementarities and exploit physical phenomena in new ways (Arthur, 2009 cited by Cantner & Vannuccini, 2012). Economists have long dealt with the issue of long-term growth on aggregate fluctuations incrementally but, according to what has historically happened, a change of this type can also occur in bursts following the introduction of a new basic technology (Durlauf & Blume, 2010).
The economy continually reconfigures itself around these technologies by changing its work logic in an evolutionary process of change that has no end. As seen, such heterogeneity has led to the introduction of the concept of General Purpose Technologies (GPTs). Potentially providing explanations for long-term macroeconomic growth periods. Each epoch,

for example, can be crossed by a single drastic innovation, which is followed by a series of incremental innovations, which lead to the characterization of long periods of economic development (Schumpeter, 1912; Kondratieff & Stolper, 1935 both cited by Teichert, 2017). Furthermore, being usable for a wide variety of applications in different markets, they have wide-ranging and transversal applicability, making GPTs the real engines of economic growth: in fact, they trigger innovation mechanisms, contribute to increasing overall productivity levels and they favour the specialization of the most advanced forms of work. In short, they represent a driving force for the economy as a whole (Gambardella, Conti & Novelli, 2020).

Contrary to the hypothesis that technological change occurs at a constant rate within the economy, GPTs are defined as difficult to predict and bear revolutionary innovations at any time (Lipsey, Carlaw & Bekar, 2005). Differing to popular belief, therefore the fact that GPTs can act as growth engines is a direct implication of the new growth-based theory, since economies of scale exist in the invention (Bresnahan & Gambardella 1998, cited by Teichert, 2017). Furthermore, from a microeconomic point of view, GPTs could also be interesting in relation to technological progress at different levels of the value creation chains and at different stages of the development process with related studies. However, by investigating incentives and interdependencies, the most important prospects could be acquired by combining these two perspectives, being able to offer macroeconomic growth implications already at the micro level (Bresnahan 2010).

As recognized by multiple researchers, the first to speak indirectly of GPTs was Paul A. Davis in the early 1990s (Ruttan, 2008; Jovanovic & Rousseau, 2005; Cantner & Vannuccini, 2012; Crafts, 2004) and then lead to the coinage of the term General Purpose Tecnology by Bresnahan and Trajtenberg, who developed and deepened the concept in 1992 and later in 1995 (Cantner & Vannuccini, 2012; Rossi, 2006). Nowadays this concept is heavily used in dealing with topics related to the role of technology and economic growth (Jovanovic & Rousseau, 2005) and, according to Rosenberg and Trajtenberg (2004), they are the representation of technologies for general purposes which are defined as key technologies and give shape to a technological era which is characterized by a presumed use in a wide range of sectors.

1.2 Characteristics of General Purpose Technologies (GPTs)

Bresnahan and Trajtenberg (1995) argue that GPTs must have some fundamental features that allow to compare and determine them among themselves. Their research will then be used as an applicable basis in the study of GPTs, in order to define and subsequently distinguish them (Jovanovic & Rousseau, 2005). Also, other authors as they have proposed descriptive solutions with similar characteristics present in the grouping of scientific writings by Helpman (1998) and in the articles by Lipsey, Carlaw and Bekar (2005), Guerrieri and Padoan (2007) and Jovanovic and Rousseau (2005) (Cantner & Vannuccini, 2012). However, the three main characteristics described by Bresnahan and Trajtenberg (1995) are the following:

1. **Pervasiveness**: GPT should spread in most sectors. This means that GPTs are used as input by a wide range of sectors for a possible and disparate application. All this is allowed by the fact that GPTs perform a generic function for which its application seems to be universal in the whole economy (Helpman & Trajtenberg, 1994). According to Lipsey, Bekar and Carlaw (1998), this type of variety and breadth of use throughout the economy is a characteristic that has undergone evolution over time. It is good to point out that GPTs often emerge as specific technologies for a specific sector and slowly spread throughout the economy (Bresnahan & Tratjenberg 1992). A new GPT has a rather specific use which tends to expand whenever new applications are discovered. The result is that therefore a General Purpose Technology is suitable for appliances in different industrial sectors and can be used with little adaptation or it is possible to make investments in its adaptation to a specific product or use (Helpman, 1998).

2. **Improvement**: GPT should improve over time and therefore should remain low and bear the costs of its users. Consequently, international efforts and learning effects will increase GPT performance over time (Bresnahan & Tratjenberg 1992). The image that emerges is that the General Purpose Technologies, in their first appearance, are considered rather rough, to then evolve into more complex technologies and widely applied in different applications. The temporal condition allows technologies to improve, reducing operating costs in the areas of use, increasing their value thanks to the invention of supporting technologies allowing the main range of use to expand and increase the variety of its practices. For this reason, a new GPT is in charge of being subjected to a research program in order to be improved, adapted and modified

(Lipsey, Bekar & Carlaw, 1998). It is therefore defined as "technological dynamism" in which innovative efforts and learning effects increase the efficiency of the generic function of the GPT (Bresnahan & Tratjenberg, 1992). It follows, as stated by Lipsey, Bekar and Carlaw (1998) that the processes of technological change and diffusion are interspersed in time, space and function.

3. **Generation of innovation**: GPT should facilitate the invention and production of new products or processes in a complementary and innovative way. Consequently, because of this functioning, the GPTs have been defined by Bresnahan and Tratjenberg (1992) as "prime-movers", to define that the productivity deriving from research and development increases as a consequence of the GPT. Furthermore, this type of technology is economically advantageous because it facilitates complementary innovations. It follows that the economic contribution provided by GPTs goes far beyond the expected return from capital investments made in technologies (Brynjolfsson & Hitt 2000). What has been seen so far is explained by the fact that, in the short term, returns represent the direct effects of technological investments, while long-term returns represent the effects of technologies combined with the related investments in the organizational field. The benefits of the technologies can therefore be fully understood unless the related technologies, capital goods and other factors cooperating with the new technology are altered, leading to changes that generally take the form of new inputs, new products and new production functions (Lipsey, Bekar & Carlaw, 1998). The real drivers of the GPTs contribution, as stated by Brynjolfsson and Hitt (2000), derive from complementary factors such as new business processes, new skills and new organizational and sector structures.

Jovanovic and Rousseau (2005) specify that most of these features are usually owned by technologies and that therefore a GPT cannot differ qualitatively from these other technologies. In addition, the third and first properties have common elements but are defined individually to affirm that GPT should also extend to the innovation sector. The second property, on the other hand, suggests a great technological dynamism given by the continuous efforts that increase over time the efficiency with which the generic function is carried out, also bringing additional users to adopt and exploit the GPT which has been further improved in other production sectors (Rosenberg & Trajtenberg, 2004). Bresnahan (2010) states, referring to what has been seen above, that the combination of second and third points is called "innovative complementarities" (IC) and that here, more precisely, IC implies that innovations in GPT increase the return in each application sector (AS) and vice versa. Therefore, technical progress in the GPT promotes and makes possible progress in a wide spectrum of application sectors which in turn increase the demand for the GPT itself, which makes further investments unnecessary to improve it, leading to the closure of a positive cycle that involves a rapid and sustained growth (Rosenberg & Trajtenberg, 2004).

The interactions between AS and GPT are not outlined. The basic structure of a GPT does not specify in which sector of application it will interface and could therefore be in goods and services in different ways. Taking as reference the examples proposed by Bresnahan (2010), the GPT could be disembodied knowledge (as in the example of the factory system or mass production), or it could be embodied in a good or service purchased by the application sectors (such as in the field of computer science). If incorporated into a capital asset, this could be purchased from the application sectors (such as a computer or electric motor) or, alternatively, the services of that capital asset could be sold by a GPT firm to each AS (such as railroad tracks). These alternatives are related but distinct from the question of how inventions are financed in GPT and AS. GPT can be in the public domain, controlled by a single company with a patent or trade secret, or provided by a large number of different companies each of which has distinct versions. The same set of alternatives applies to the AS; application technology may or may not be disincarnated, protected or not by patents or trade secrets and provided to the AS by a specialized company or not. The invention in the AS can therefore be undertaken by each company in the AS or a specialist can emerge to provide a technological good (Bresnahan, 2010).

If on the one hand the definition proposed by Bresnahan and Trajtenberg (1995) turns out to be the most used and exploited also as a basis by numerous authors, on the other hand, other publications are equally interesting. In fact, according to Cantner and Vannuccini (2012), the model of Jovanovic and Rousseau (2005), which uses the model previously seen as a starting point, turn out to be an interesting evolution. Jovanovic and Rousseau (2005) in addition to the basic characteristics of GPT, which through empirical analyses prove correct, include more subtle and less direct aspects that emerge from the theoretical work on GPTs and which will also be part of theories proposed later. These models predict the following outcomes:

- **Productivity should slow down**: New technology may not be intuitive initially and production may decline for a while as the economy adapts.

- **The first prize should arise**: If the GPT is not suitable for users first, qualified people will be more in demand when the new technology arrives, and their earnings should increase compared to those of the non-qualified.

- **Entry, exit and mergers should increase**: These are alternative ways of reallocating assets.
- **Share prices should initially drop**: The value of old capital should drop. The speed with which it drops depends on how the market learns of the arrival of the GPT.
- **Young and small businesses should do better**: GPT-associated ideas and products will often be introduced to the market by new businesses. The market share and market value of young businesses should therefore increase compared to older ones.
- **Interest rates and trade deficit**: The increase in desired consumption relative to production should increase interest rates or worsen the trade balance.

1.3 Innovative Process and Growth Through GPT

General Purpose Technologies take a long time to have a significant impact on economies and society (David, 1989; Lipsey, Bekar & Carlaw, 1998) and there must be incremental improvements on these technologies for them to have an impact (Nuvolari 2004). In addition, systems and technologies complementary to the main technology must also be developed, which however are not limited in any way to technology for general purposes. In order to realize its potential in a society, the GPT must, to a large extent, be subjected to incremental improvements made to technology and subsequent development of complementary systems technologies (Allen, 2009; Mokyr, 1990; Rosenberg1979, all cited by Shimizu, 2019). These incremental improvements are essential to be able to take advantage of their versatility and applicability, as GPT development needs further improvements (Shimizu, 2019). For this reason, economists agree that technological change has been the determinant of modern growth since the 1990s. The GPT has therefore allowed to contextualize the relationship between technology and growth. It follows that GPTs are seen as rare but pervasive exogenous technological shocks, which allow to generate positive low-frequency effects on economic growth by transforming the productivity potential of economies (Jovanovic & Rousseau 2005).

As it will be possible to observe, the work of Bresnahan and Trajtenberg (1992) was of fundamental inspiration for the delineation of the phenomenon and the impact of a General Purpose Tecnology and below will be proposed the models which, after the one mentioned above, provide an analysis formal GPTs using endogenous growth theory and related models (Lipsey, Carlaw & Bekar, 2005).

As previously seen Bresnahan and Trajtenberg (1992) argue that the technologies have a structure similar to that of a tree, with "prime movers" at the top that establish a research program for subordinate and complementary technologies. From their model it is possible to appreciate how a GPT is used as a component in many downstream sectors because it provides a generic function. In addition, there is support for learning and innovation in a GPT research program.

Ultimately, the mutual reinforcement of the productivity increases generated by its downstream applications and vice versa will lead to an increase in productivity generated by the GPT. The consequences expected from the improvement of the GPT will therefore allow a reduction in the costs of applications in the applications sector, the improvement of downstream products and the adoption of GPT in a growing range of downstream activities. It is therefore deduced how the GPT improvement decisions induce more innovative efforts in the applications sector, feeding them through complementarity to induce further improvements in the GPT. According to Lipsey, Bekar and Carlaw (1998), this complementarity feature can be considered the result of the first two features of the previously seen model, as GPTs provide inputs that satisfy various uses and are probably at the centre of technological systems, being connected to many other technologies. In general, it can be said that the more pervasive a technology is, the more it is expected to behave with others and for this reason, innovations in GPTs will generally induce major structural changes in many, sometimes even in the great majority of other technologies.

However, Bresnahan and Trajtenberg (1992) define a potential coordination problem between research and development applied to GPTs given the information asymmetries and coordination errors but also define a horizontal complementarity between the downstream sectors, for which each application sector benefits from the addition marginal of another application sector due to the positive effect that this has on the quality of the GPT. This second aspect, however, creates another coordination problem that leads the authors to important assessments on intellectual property, evaluating how policies with strong protection of the intellectual property of a GPT could reduce horizontal externalities and therefore limit the precious development of complementary downstream technologies.

As stated by Cantner & Vannuccini (2012), in this model, deriving from a micro/industrial structure and representing the interaction between two types of sectors, the GPT sector and a series of application sectors (AS), as a strategic game that leads to balance of Nash, cannot be properly considered a growth model.

In addition to the Bresnahan and Trajtenberg models (1992) there are other models that provide a formal analysis of GPTs using endogenous growth theory and are Helpman and

Trajtenberg (1994, 1996) and Aghion and Howitt (1998) (Lipsey, Carlaw & Bekar, 2005). These models just mentioned are considered first generation models and are distinguished from a second generation which will be analysed later (Cantner & Vannuccini, 2012).

Helpman and Trajtenberg (1994), on the basis of what has been seen previously, extend the technological tree of Bresnahan and Trajtenberg using a general framework of balance to be able to trace the effects of a new GPT in macro aggregates and model the diffusion process of a new one GPT: GPT productivity depends on the number of support components that are created by the research and development sector and produced in a certain quantity that will lead them to be used together with GPT in the final output sector. It is used until enough complementary component units have been developed to make it more productive than the historical GPT. In the Helpman and Trajtenberg model (1994), the production function has the property that when new complementary components are added, the total output increases while the productivity per component decreases leading to a finite limit to the trajectory of technological development of the GPT.

In comparison with what was expressed by Bresnahan and Trajtenberg, it emerges that the proposed model contains vertical complementarity between GPT and its support components and a type of horizontal substitutability between the support components themselves, leading to the replacement of their innovative complementarities that referred to complementarity strategic and proprietary GPT and application sectors that use GPTs. As observed by Lipsey, Carlaw and Bekar (2005) the components developed for a particular GPT replace each other, a statement that would be true for some technologies but certainly not true for many of the sub-technologies of a given GPT that could be complementary. Helpman and Trajtenberg (1994) therefore reversed the horizontal complementarity of Bresnahan and Trajtenberg and, as observed by both pairs of authors, the GPTs are themselves components of their application technologies. It follows that GPT evolves into components of a wider range and a variety of applications, no longer using components developed as inputs for it.

Upon the arrival of a new GPT and its subsequent recognition, according to Helpman and Trajtenberg (1994), two things can happen: firstly, if the research and development activity surrounding the old GPT had already produced all the components economically valid, then all resources in the economy are devoted to production. Therefore, the new research and development activities divert resources from production causing a temporary slowdown in the measured output. Secondly, if the new GPT arrives while the components are still under development for the old GPT, the research and development relating to the old technology stops immediately and resources are diverted both from research and development for the GPT in charge and from the production sector to research and development for the new GPT, causing a slowdown on exit. Consequence to two previous cases, in the end enough components are developed so that the productivity of the new GPT exceeds that of the old GPT and the production activity passes from the use of the old GPT to the use of the new one. As can be seen, these are the effects of growth that make GPTs, by their nature, different from other technological changes. Helpman (2004) also states that:

> Growth that is driven by general purpose technologies is different from growth driven by incremental innovation. Unlike incremental innovation, GPTs can trigger an uneven growth trajectory, which starts with a prolonged slowdown followed by a fast acceleration. (Helpman, 2004, p. 51 cited by Ristuccia & Solomou, 2010).

In a subsequent publication, Helpman and Trajtenberg (1996) model the process of spreading a new GPT. Therefore, they define that it can potentially be adopted by many sectors with different productivity in using it. Sectors with the same productivity would consequently have in GPT an instant diffusion in all sectors as soon as the number of components created in the research and development sector were sufficient to induce anyone to use it. Each sector develops components for the GPT in sequence, diverting resources from production to research and development, starting with the one that has more to gain from the new GPT. Following the initial research and development, each sector, with the exception of the final one, waits until the completion of the last phase of research and development of the economy for the adoption of the GPT, therefore all join the research and development process for complete the final stage. As specified by Lipsey, Carlaw and Bekar (2005), the Helpman and Trajtenberg model is actually one of diffusion in terms of research and development activities, not in terms of GPT implementation. The diffusion process of research and development drags the dynamic model in the passage from one GPT to another.
Since their subsequent analysis is based on Helpman and Trajtenberg (1994), Helpman and Trajtenberg (1996) maintain counterfactual assumptions that all components are substitutes for each other and that the components of the application sector are used as GPT input instead of as GPT used as an input component for applications developed in downstream sectors.
In their book Lipsey, Carlaw and Bekar (2005), discussing the growth resulting from GPTs, they quote Aghion and Howitt (1992) who, although they do not develop a GPT model, develop a model of technological change and creative destruction. Being a model of endogenous technological change that addresses the issue related to modelling the arrival rate of

technology and, moreover, employing modelling techniques to deal with endogenous technological changes can be a source for the construction of models of GPTs.

Aghion and Howitt (1992) in their model present a stationary equilibrium whose rate of innovation is determined by the expected value of a Poisson arrival process,[1] where the arrival rate is determined by the effort of equilibrium work dedicated to the discovery of new technologies and a parameter of the Poisson distribution. The innovations will therefore come at a continuous speed determined by the stationary equilibrium and the size of productivity gain associated with an annual innovation with the effort to create larger innovations and is balanced on the margin compared to the expected costs. Costs are opportunities for obtaining rents for smaller innovations and, according to what they assume in their model, the advent of larger innovations takes place with less probability and the opportunity cost increases with the size of the innovation.

Lipsey, Carlaw and Bekar (2005) say that the characterization proposed by Aghion and Howitt (1992) on the impact on productivity is different from what has been observed in reality where different technologies have different and often unexpected impacts. However, the authors' goal was to develop a model of economic growth that takes into account the creative destruction that occurs as a result of endogenous decisions.

In a subsequent work, Aghion and Howitt (1998) began the discussion of two of the problems of empirical relevance in Helpman and Trajtenberg (1994). In the first analysis, the times of the slowdowns occur immediately upon the arrival of the new GPT, they are incompatible since it would take several decades for a new technology of greater scope to have a significant impact on macroeconomic activity. In the second analysis, they argue that the reallocation of research and development work when GPT arrives may not be large enough to cause a slowdown in productivity of the kind seen in reality. Aghion and Howitt (1998) therefore define a model on which three distinct phases are delineated, the first of which proposes the arrival of the GPT, but the output remains constant given that measurement errors, complementarity and the concept of social learning are assumed.

As in the Helpman and Trajtenberg model (1994) each sector creates final production engages in research and development to make sector specific components for the GPT before it can be used in that sector but, differently, each sector must first acquire a model to associate to the GPT before the industry can begin the component development process. Enterprises can acquire the model through independent discoveries using their own research and development or by imitating other companies that observe. Their research and

[1]The Poisson process is a stochastic process that simulates the manifestation of events that are independent of the one from the other and that happen continuously over time.

development are conducted by sectoral workers who have no other use. Nothing changes in the aggregates measured during the model detection phase because no resources have been reallocated, so there is no change in the output. The initial probability that a company in any sector can discover its model on its own is low. But the probability of acquiring a model increases as discoveries are made because businesses can imitate by observing the successes of other companies. Hence, the more models have been discovered, the greater the probability of success for those companies that have not yet made the discovery, and therefore the model discovery rate accelerates over a certain interval. When a company discovers its model, it enters the second phase which is represented as the first phase of the Helpman and Trajtenberg model (1994) and once the model is discovered, the companies move the resources of the output production to research and development to produce the components defined by the model and necessary for the implementation of the GPT. The diversification of the work resources above causes a reduction in production and the speed with which companies discover an implementation of their research and development spurs is an increasing function of the number of companies in the second phase and a random arrival process at Poisson.

The third phase occurs after companies successfully discover an implementation and hence the growth in output occurs. Generalized work is therefore the constraint of resources, each of which can produce a unit of the component or an output based on the production function.

Aghion and Howitt (1998), like Helpman and Trajtenberg (1994), assume that components are created for GPTs, rather than the GPT being a component in a wide range of applications, and therefore face the same issues as all components are substitutes instead of some complements, so that the intuition of how a GPT works when it enters a production system is reversed by what is observed.

Aghion and Howitt (1998) argue that the second problem is relatively easy to deal with because a massive and fundamental change in technology would cause adjustments and coordination problems. They declare that they present themselves as changes in undeclared capital, an increase in the rate of turnover of labour due to higher rates of innovation and an accelerated rate of obsolescence. They do not model this undeclared cost problem.

According to Lipsey, Carlaw and Bekar, (2005) the literature on historical and appreciation theories of GPTs and other similar concepts covers broad views of major technological changes that drive socioeconomic and structural change. This literature does not provide formal models but is full of complex details on how technologies in general and GPTs in particular can have revolutionary effects on entire economies. A common theme is that the

evolutionary process dependent on the path that generates GPT and therefore integrates them into the economic system is complex and full of uncertainty.
In fact, the models just presented represent the first generation and, below, some models of the second generation will be presented. The distinction between the different models is more conceptual and chronological in nature since the second generation represents a temporary recovery of the topic after its initial rapid success followed by an equally rapid loss of interest in the late 1990s; it must be taken into account, however, that the first generation GPT-based models share a common assumption: GPT is recognized ex ante as a general-purpose technology and, therefore, economic agents have only the opportunity to decide, based on the expected profit, resulting from the allocation of resources to research. (Cantner & Vannuccini, 2012).
Following this definition, it is possible to insert the van Zon, Fortune and Kronenberg (2003) model which, even if it presents characteristic gaps of the first generation, is the first to allow the coexistence of GPTs (Cantner & Vannuccini, 2012).
The authors deal with two types of research and development processes according to the Poisson process: first, a basic research and development sector, which produces core technologies (GPT) and, secondly, an applied research and development sector, which produces peripherals, corresponding to the components used by Helpman and Trajtenberg (1994). Both research and development sectors are subject to decreasing returns, therefore following the arrival of a basic technology, the economic incentive, and consequently the workforce, switches to peripheral production and vice versa. The fundamental novelty in the model, represented in a simulation study, concerns the possibility that some key elements become "failed" GPTs if a small or zero number of components is developed for them. Failed GPTs allows to define that during the innovation process, true pervasiveness can only have a hypothesis, making its arrival and its creation hypothetical. A GPT is an "ex post mental construct", which derives from the evidence that a particular technology is capable of performing a wide range of new, but also existing, functions for productivity in the economy; contrary assumptions, may lead to a limited understanding of GPTs-based economic growth. (van Zon, Fortune & Kronenberg, 2003).
In 2006 Carlaw and Lipsey developed and expanded what Van Zon, Fortune and Kronenberg (2003) suggested, proposing a model with three unbalanced competitive factors, in which the appearance of a GPT is driven by an endogenous mechanism. The three sectors represented are each represented by a specific production function and are:

1. A fundamental research sector that accumulates a wealth of basic knowledge and produces GPT;

2. An applied research and development sector;

3. A consumer sector.

Teichart (2017), analysing in detail what illustrated by Carlaw and Lipsey (2006), perceives how the consumer sector, illustrated in point three, produces consumer goods with a level of productivity that derives for a part of the knowledge generated by the research sector applied development, allowing the accumulation of knowledge with an efficacy that depends on the stock of knowledge available in the field of fundamental research. On the other hand, the fundamental research sector creates knowledge related to GPTs with a productivity that depends on the share of applied knowledge which however is not directed towards the production of consumer goods. The arrival of a new GPT is again stochastic and is modelled on a mechanism that presents major complications compared to the Poisson process that has been used in the processes seen previously: two beta distributions generate two random values; the former is compared to a threshold and, if greater, GPT is displayed. The second serves to evaluate the share of new fundamental knowledge that affects the sector applied as a productivity term. Finally, the model is closed with assumptions about consumer expectations, a problem of maximizing and allocating resources.
In the following years, Carlaw and Lipsey (2011) further developed the model in a series of studies that conclude with multiple and coexisting GPTs active in the economy.
Cantner and Vannuccini (2012), despite subsequent theoretical developments, consider the initial approach followed by Bresnahan and Trajtenberg (1992), as the most promising starting point for tackling the GPTs. The common feature of all these models is that the reallocation of resources towards research and development in the field of newly arrived GPT can produce a slowdown in productivity due to the delay in the production of research and the related non-payment. Here the economic growth phase comes when research efforts translate into GPT economic returns, however, once the initial losses are overcome, a positive aggregate economic growth occurs (Jovanovic and Rousseau 2005), which reaches its peak when all applications in some sectors went through the investment phase without returns in order to subsequently contribute positively to aggregate economic growth (Teichert, 2017).

1.4 Types and Historical Periods of Recognized GPTs

As expressed by Lipsey, Carlaw and Bekar (2005), there are only 24 technologies that, since the agricultural Neolithic revolution, can be classified as true GPTs because they meet four characteristics listed below:

1. They are a unique and recognizable generic technology;
2. Initially they have a lot of room for improvement, but are widely used throughout the economy;
3. They have many different uses;
4. Create many spillover effects.

From the list proposed below, it is possible to observe how the Information and Communication Technologies (ICTs) are revolutionary in the current period, but it should be noted that there have been other "new economies" led by other GPTs in the past. Furthermore, GPTs have not been common to human experience because they have averaged two or three per millennium in the past 10,000 years. On the other hand, however, it is possible to observe how the rate of innovation of GPTs is continuously accelerating during the whole period. In fact, it is noteworthy that since the eighteenth century there have been two important GPTs, four in the nineteenth century and seven on the following one. The time from the first discovery to a fully developed GPT has also been accelerated, though not uniformly. Indeed, discoveries such as iron and water wheel took hundreds of years to find widespread and multipurpose use while from the nineteenth century onwards, the gestation period between the first introduction and emergence as a complete GPT was typically measured in a few decades.
These technologies fall into six main classes, with no overlapping but it should be borne in mind that at any time there may be multiple existing GPTs and even more than one in a particular class due to the multiplicity of use. The classes always prepared according to Lipsey, Carlaw and Bekar (2005) are the following:

- **Materials technologies**: domesticated plants, domesticated animals bronze, iron, biotechnology.
- **Power**: domesticated animals, waterwheel, steam engine, internal combustion engine, dynamo.
- **Information and communications technologies**: writing, printing, computer, Internet.
- **Tools**: wheel.

- **Transportation**: domesticated animals, wheel, three-masted sailing ship, railway, iron steamship.
- **Organization**: factory system, mass production, lean production.

Even dating a GPT is not easy and refers to what is meant by dating. Some innovations such as electricity or microprocessors were already available before their classification, but time has passed from their discovery to their classification. It should be noted that, however, taking as an example the two innovations mentioned above, their discovery did not lead to productivity increases and therefore their effective definition in GPTs was postponed when there was an increase in productivity and a multisectoral diffusion and mass (David, 1989; Durlauf & Blume, 2010; Bresnahan, 2010; Bekar, Carlaw & Lipsey, 2018).
The Table 1.1 below summarizes the General Purpose Technologies identified by Lipsey, Carlaw and Bekar (2005) and collected in chronological order, classified by type and defined on the basis of the spillovers made.

Table 1.1: Transforming GPTs (Lipsey, Bekar & Carlaw, 1998 p. 132).

GPT	Spillover Effects	Date	Type
Domestication of plants	Neolithic Agricultural Revolution	9000-8000 BC	Process
Domestication of animals	Neolithic Agricultural Revolution, Working animals	8500-7500 BC	Process
Smelting of ore	Early metal tools	8000-7000 BC	Process
Wheel	Mechanization, Potter's wheel	4000–3000 BC	Product
Writing	Trade, Record keeping	3400-3200 BC	Process
Bronze	Tools & Weapons	2800 BC	Product
Iron	Tools & Weapons	1200 BC	Product
Water wheel	Inanimate power, Mechanical systems	Early Middle Ages	Product
Three-Masted Sailing Ship	Discovery of the New World, Maritime trade, Colonialism	15th Century	Product
Printing	Knowledge economy, Science education, Financial credit	16th Century	Process

GPT	**Spillover Effects**	**Date**	**Type**
Factory system	Industrial Revolution, Interchangeable parts	Late 18th Century	Organisation
Steam Engine	Industrial Revolution, Machine tools	Late 18th Century	Product
Railways	Suburbs, Commuting, Flexible location of factories	Mid 19th Century	Product
Iron Steamship	Global agricultural trade, International tourism, Dreadnought Battleship	Mid 19th Century	Product
Internal Combustion Engine	Automobile, Airplane, Oil industry, Mobile warfare	Late 19th Century	Product
Electricity	Centralized power generation, Factory electrification, Telegraphic communication	Late 19th Century	Product
Automobile	Suburbs, Commuting, Shopping centres, Long-distance domestic tourism	20th Century	Product
Airplane	International tourism, International sports leagues, Mobile warfare	20th Century	Product
Mass Production	Consumerism, Growth of US economy, Industrial warfare	20th Century	Organisation
Computer	Digital Revolution, Internet	20th Century	Product
Lean Production	Growth of Japanese economy, Agile software development	20th Century	Organisation
Internet	Electronic business, Crowdsourcing, Social networking, Information warfare	20th Century	Product

GPT	Spillover Effects	Date	Type
Biotechnology	Genetically modified food, Bioengineering, Gene therapy	20th Century	Process
Nanotechnology	Nanomaterials, Nanomedicine, Quantum dot solar cell, Targeted cancer therapy	21st Century	Product

It should be noted that Artificial Intelligence (AI), the subject of this thesis, was not added to this table because it was considered one of the most recent GPTs but not yet developed and introduced during the writing of the Lipsey, Bekar and Carlaw table. In fact, according to Shimizu (2019), Artificial Intelligence, by its nature, can certainly be considered a GPT because its uses cover multiple applications and can possibly increase productivity in the entire economy.
Artificial Intelligence like GPT will therefore be the topic of analysis of the next chapter and will be treated in all its aspects.

Chapter 2

Artificial Intelligence (AI)

2.1 Definition

Artificial Intelligence (AI) is the branch of computer science that studies the development of hardware and software systems endowed with the typical capabilities of the human being and is able to autonomously pursue a defined commitment by making decisions that, up to that moment, were usually entrusted to people. The typical abilities of individuals concern, specifically, the understanding and processing of natural language (NLP - Natural Language Processing) and images (IP - Image Processing), learning, reasoning and the ability to plan and interact with people, machines and the environment (Gianni, 2020).
Gardner (1999, cited by Kaplan & Haenlein, 2019) define Artificial Intelligence taking as a reference point human intelligence which has the possibility to assume the meaning of biopsychological potential to process information, to solve problems or create products that have value in a culture. McCarthy et al. (2006), retracing the historic article presented at the 1955 Dartmouth Summer Research Project (further detailed below) configure machine behaviour in ways in which human behaviour itself can be intelligent. The relationship between man and machine is represented even more in depth by the thought of Minsky (1968, cited by Kaplan & Haenlein, 2019) who prefers a definition in which machines perform tasks for which a human counterpart would need intelligence. More recent definitions would seem to focus more on the way in which this goal is achieved by defining AI as the ability of a system to attribute a correct interpretation of data, to learn from such data, and to use such learning to achieve specific objectives and tasks through a flexible adaptation (Kaplan & Haenlein, 2019). According to Gianni (2020) and Boldrini (2020), from a literary point of view, there is no single definition of AI and the interpretations can vary

depending on the focus. On the one hand, we can focus on the internal processes of reasoning, on the other hand on the external behaviour of the systems, in principle always taking the similarity or proximity to human comportment as a sort of "measure of effectiveness". The authors, starting from these considerations, affirm how the scientific community has found agreement in defining two different types of Artificial Intelligence, the weak and the strong:

- **Weak AI**: it contains systems capable of simulating some human cognitive functions without however achieving the intellectual abilities typical of humans; broadly speaking, these are problem-solving programs capable of replicating some logical human reasoning to solve problems, make decisions, etc.

- **Strong AI**: systems capable of becoming wise (or even self-conscious) are included in this category; there are theories that lead some scientists and experts to believe that one day machines will have their own intelligence (therefore they will not emulate that of man), autonomous and probably superior to that of human beings.

The systems currently in use fall within the scope of weak intelligence, but progress is constant. Weak AI and strong AI classification underlie the distinction between Machine Learning and Deep Learning. What characterizes Artificial Intelligence from a technological and methodological point of view is the learning method/model with which intelligence becomes proficient in a task or action. These learning models are what delineates Machine Learning and Deep Learning specifically (Boldrini, 2020).
Machine Learning (ML) which, as a branch of AI, uses methods or algorithms for the automatic creation of models from data. Unlike a system that performs an activity following explicit and predefined rules, a Machine Learning model constantly learns from experience. Conversely, a system based on predetermined rules will perform a task every time in the same way while the performance of a Machine Learning system can be improved through learning, exposing the algorithm to a greater amount of different data (Heller, 2020). This amount of data and learning serve to "train" the software so that by correcting errors it can learn to carry out a task/activity independently (Gianni, 2020; Brynjolfsson, Rock & Syverson, 2017). Boldrini (2020) states that the main feature of Machine Learning is based on its learning model and it is precisely on the basis of it that a sort of classification of algorithms can be done:

- **With didactic supervision**, that is learning through examples of inputs and outputs to make AI understand how it should behave;

- **Without didactic supervision**, that is learning by analysing the results: in this case, the software understands how to act, and the learning model adapts on the basis of outputs that allow mapping the results of certain actions and tasks that the software will be required to perform);
- **Reinforcement learning**, that is "meritocratic" learning: AI is rewarded when it reaches objectives, results, performs an action, etc. This way it learns to define which actions are correct and which are wrong.

After ML, Deep Learning (DL) is emerging, which is itself a sub-category of Machine Learning. It represents learning by "machines" through data studied across the use of algorithms (mainly of statistical calculation). Deep Learning, in fact, is part of a broader family of Machine Learning methods based on the assimilation of data representations, as opposed to algorithms for the execution of specific tasks (Boldrini, 2019). The DL is inspired by the structure and functioning of our brain, emulating the human mind. In this case, the mathematical model alone is not enough: Deep Learning requires ad hoc artificial neural networks (detailed below) and a very powerful computational capacity capable of "supporting" different layers of calculation and analysis (Gianni, 2020). Deep Learning architectures represent, for example, applications in computer vision, automatic recognition of spoken language, natural language processing, audio recognition and bioinformatics (Boldrini, 2019).

2.2 History of AI

Artificial Intelligence (AI) is of great interest from a technological point of view but it does not represent a new field of study, since lays its foundations in the 1950s, which in turn is based on a path of philosophical reasoning started in the ancient Greek period by Hobbes, Leibniz and Pascal (Corea, 2017). Historically, 1956 is remembered as the start of the field of Artificial Intelligence research, following a seminar held on the Dartmouth College campus in the summer of that year (Corea, 2017). The official beginning of AI took place only a few years after Asimov's creation of the laws of robotics but also after the historic article by Turing (1950), where the idea of a thinking machine was conceived, i.e. capable of continuing a conversation indistinguishable from that of a human being, together with the well-known homonymous criterion for determining whether a machine is capable of exhibiting intelligent behaviour, determining the first serious proposal in the philosophy of Artificial Intelligence (Russell & Norvig, 2010; Corea, 2017).

The Dartmouth conference was organized by Marvin Minsky, John McCarthy along with two senior scientists Claude Shannon and Nathan Rochester. Where the basic idea was described by the statement *"every aspect of learning or any other feature of intelligence can be so precisely described that a machine can be made to simulate it"* (McCarthy et al., 2006, p. 12). The success of the conference favoured significant investments in the sector bringing numerous funds that allowed the creation of multiple development programs (Haenlein & Kaplan, 2019). Around the same time, there was also a hype from people who thought the problem-solving abilities of various kinds were surprising, in particular towards intelligent behaviour by the machine (Russell & Norvig, 2010). All this enthusiasm then transformed in intense optimism on the part of researchers who saw the creation of a fully intelligent machine over the next twenty years and for the next two decades there was significant success in the field of AI (Haenlein & Kaplan, 2019; McCorduck, 2004).
However, the expected results were not achieved, the first signs of the crisis in the sector occurred as early as 1966 when the ALPAC[1] report criticized AI's machine translation efforts despite the 20 million spent (McCorduck, 2004; Russell & Norvig, 2010). Despite the hefty investment outlay, the NRC[2] ended all support. Starting as early as 1973, the United States Congress strongly criticized the huge spending on AI research. Across the ocean, more precisely in Great Britain, a study (the Lighthill Report of 1973) questioned the feasibility expectations of a machine with strong intellectual abilities, leading the British government to stop much of the university research in progress. The US government subsequently made the same choice (Haenlein & Kaplan, 2019; Russell & Norvig, 2010). These two events, together with the scarcity of data available to feed the algorithms and the poor computational capacity, disrupted the AI industry that fell out of favour and created the so-called "AI Winter" (Corea, 2017). According to Corea (2017), this phenomenon of decreased trust and funding is called the "AI effect" and consists of two characteristics:

1. The constant promise of true AI coming in the next decade;

2. The actualization of AI behaviours after overcoming a certain problem, continually redefining the meaning of intelligence.

Also in the 1970s, the Machine Learning (ML) discourse came to life in response to the

[1]The ALPAC (Automatic Language Processing Advisory Committee) report is a document that raised many doubts about the creation of the perfect automatic translator which, in the USA, was financed by the Defense Advanced Research Projects Agency (DARPA) (Corea, 2017).

[2]Acronym for National Research Council, the formal name by which the program units is known, which is an academic set of political consultancy.

failure of rules-based approaches in which human experts encoded knowledge in artificial intelligence systems which, however, due to their basic functionality did not get interest from researchers, curiosity that is currently growing strongly (Klinger, Mateos-Garcia & Stathoulopoulos, 2018, citing Markoff, 2016). In the 1980s, a new form of Artificial Intelligence took hold: the expert systems. It soon became an element adopted by companies around the world, making knowledge of the basic element of artificial AI. To make the sector attractive again were the huge investments by the Japanese government which were subsequently followed by investments from the US side through DARPA (Moravec, 1994; Haenlein & Kaplan, 2019). These new development programs, which operated in specific sectors, were able to simulate a new financing trend where the strong will to reach the fifth generation computer[3] by the Japanese government made, indirectly, resume investments and interest from some of the states that already in the past were heavily involved in the study and research of Artificial Intelligence, which were mainly Great Britain and the United States (Corea, 2017). From this Japanese expedient, the discourse of neural networks came to life, by nature similar to the actual functioning of neurons, which constitute a part of the historical and developmental discourse of AI and consequently of ML(Mayo et al., 2018). However, research on the neural network was abandoned by computer and Artificial Intelligence researchers, causing a schism between AI and ML. Until then, Machine Learning had been used as a training program for AI (Foote, 2019).

The fascination generated by Artificial Intelligence suffered a further decline in interest in the 1980s as a result of the classic financial speculative bubble. What collapsed was governments' positive perception of investors leading to the disruption of funding. AI then slowed further (Moravec, 1994). This period of crisis is associated with the second AI winter, one of the main causes is attributable to the computing power acquired by Apple and IBM computers which, thanks to constant improvements, were able to drill better than expensive AI machinery (McCorduck, 2004).

According to Haenlein and Kaplan (2019), the lack of progress that occurred at the beginning in the field of Artificial Intelligence and that the reality of the programs, developed to be able to replicate human intelligence, is different from the expected prospects is to be referred to the fact that the Expert systems developed up to the 1970s are based on rules that assume that human intelligence can be described from top to bottom through the "if-then" assumption. Although in some applications they are very effective, expert

[3]The Fifth Generation Computer Systems (FGCS) was an initiative by Japan's Ministry of International Trade and Industry (MITI), to create computers using massively parallel computing and logic programming (Shapiro, 1983).

systems perform poorly in sectors that do not lend themselves to such formalization. The effectiveness of the AI system must therefore be based on the ability to interpret a series of external data, which must be learned from the machine and, through this series of learnings and a flexible adaptation, achieve the intended goal. Haenlein and Kaplan (2019) also dwell on the fact that, since "expert systems" do not possess these characteristics, they cannot be considered real AI, contrasting with Russell and Norvig (2010) and McCorduck (2004) who consider networks experts as the first truly intelligent forms of artificial intelligence.
In the mid-1990s, AI began to be used successfully within a variety of technological systems, albeit with some applications less obvious than others. The increase in power has therefore made it possible to achieve a more diverse application even if a certain distrust in the world of investments and finance, also attributable to the two AI winters, and the failure to create an intelligence based on a purely human level, led to a focus by the AI mainly in sub-heads, applied to specific cases fragmenting their application (McCorduck, 2004). An increase in interest and progress has occurred since 1997 when the IBM Deep Blue computer, which was a computer for playing chess, beat the world chess champion (Mayo et al., 2018).
The paradigm of intelligent agents was therefore outlined, a system that perceives the surrounding environment and takes actions to maximize its chances of success. Solving specific problems, they are defined as intelligent agents as human beings are defined and their groupings, such as companies. AI is therefore defined as the study of intelligent agents which, going beyond the study of human intelligence, studies all types of intelligence (Russell & Norvig, 2010).
Within larger systems, algorithms developed by AI researchers have begun to appear, managing to solve several problems, while receiving the status of a simple IT implementation (McCorduck, 2004). According to Corea (2017), academic research has made significant developments over the past two decades, but only since 2012 has it gained widespread general recognition. Year in which a group of researchers developed, at a conference on neural networks, an improvement of an image recognition algorithm, making it better than what the human mind can achieve. To date, artificial neural networks and Deep Learning constitute what in the modern conception is identified under the label of AI and represent most of the applications of use with which people are in contact (Haenlein & Kaplan, 2019).

2.3 Present and Future of AI

The ultimate goal of Artificial Intelligence is that a machine can have a type of intelligence similar to that of humans, this representation is one of the most ambitious ever proposed by science (de Mántaras, 2018).
The development of Machine Learning would seem to be the empirical proof of the differences concerning Artificial Intelligence between today and the past. Today, the developed algorithms have the ability to read, hear or see, which in the past had to be processed in a way that the machine could understand. The turning point is given by technological advancement which therefore allows direct input of inputs without any human involvement, creating a representation inside the machine that does not require further processing. While the development of the system is appreciable, on the other, big data takes on importance. Being powerful tools, they have and will have an important development in supervised learning in which the machine learns from the data represented in input-output pairs. These large data sets have also favoured the proliferation of automatic learning systems in every application area and allow processing that was once unthinkable in conditions of purely human analysis (Dhar, 2016). The combination of algorithm processing and access to huge amounts of data has allowed us to achieve remarkable results, especially in the last decade. The further difficulty, however, is not given by the limited amount of data or by the poor performance of the algorithm but by the specificity in which Artificial Intelligence operates (de Mántaras, 2018). If the maximum objective to which an Artificial Intelligence aspires is to be general in its applicability (see the paragraph in which AI is analysed as GPT), the current development is considered as "competence without comprehension" (Dennet, 2018 cited by de Mántaras, 2018).
The current efforts for the future have been directed towards the construction of an AI capable of interacting in a free environment and not previously prepared, where there is a need for languages capable of encoding information on different detected inputs and algorithms capable of representing solidly and efficiently the new types of input, being able to re-elaborate answers able to satisfy multiple applications in multiple topics (de Mántaras, 2018). The need for AI algorithms will be to acquire data in a practically unlimited way. These systems will have to be able to learn throughout their existence and essentially, they will have to have perception, representation, reasoning, action and learning and at present, it has not yet been possible to integrate these characteristics. The integration will therefore be the necessary step to be able to obtain an AI that is configured as of general use and that therefore can reflect what is necessary to be a GPT (Forbus, 2012). However, the transitional phase will lead to the birth of hybrid systems that will benefit from the

use of systems capable of reasoning on the basis of knowledge and the use of memory by interfacing with the new evolutions of AI systems (Graves et al., 2016).
From the point of view of the intellect, although increasingly efficient, AI will never be able to replicate human intelligence. Not being able to have the same processes of socialization and acquisition of culture will by their nature always be different in some way (de Mántaras, 2018). But, although in some way they will always be different, already in the current state they are able, based on the data that we ourselves publish on the net, to deduce what and how people think and can "perceive" how they feel. Certainly, the amount of data that is produced facilitates the task of the algorithm, but currently, the challenge of AI must address the intrinsic issue of privacy and its current management difficulty. The management of the AI does not respond to these queries and conceptually it would be better to have a filtering mechanism when creating the algorithm itself. Given its nature of data analysis and poor filtering capacity, the risk for AI is also given by the creation of false news or incorrect data processing, which suggests the very limit of AI, the lack of meaning critical in facing judgments. Furthermore, a hypothetical error-free software would leave the prerequisite for wide-ranging ethical problems and media interest. (Haenlein, & Kaplan, 2019; de Mántaras, 2018). The interest from governments is high and in particular the United States government published in 2016 a report on the future developments of Artificial Intelligence and on what it expects to have a few years from now. The Table 2.1 shows the resulting expectations according to a reworking of Bundy (2016).

Table 2.1: The US government's expectations of AI (Bundy, 2016).

Advantages	AI can increase productivity, lower costs, make products and services more widely available, and provide more accuracy and precision.
Exploitation	Private and public institutions need to consider how they can take advantage of this potential of AI and hire staff to enable them to do so.
Research	The need to increase investment in AI research, particularly in basic research, where it is not in the immediate interest of the industry to invest, so the government must be involved.
Education	Raising the quality level of education to a high level.
Ethics	Integration of security and privacy to allow to put in practice good deeds.

Accountability	Difficulty in extracting explanations from automatic and statistical learning programs to be able to give explanations to multiple applications.
Privacy	Implement applications consistent with consumer privacy.
Regulation	Readiness for an incremental change in regulations when it proves inadequate. It will be the task of experts to assess and promptly anticipate changes.
Collaboration	Active collaboration with other states and companies.
Employment	Harnessing the potential to eliminate and/or reduce the wage gap in low-skilled jobs, requires measures to maintain equality and widely spread economic benefits.
Autonomous weapons	Need to develop a policy consistent with humanitarian law.
Public debate	The necessity to start a public debate on AI issues to explain the effects and issues.

2.4 AI as GPT

As seen in previous chapters, the GPTs have been able to favour, through their characteristic disruption within the economy, the transformative effects on economic history. Since there is no unanimous definition of General Purpose Technologies and being multisectorally applicable, there may be discrepancies between the groupings described by the different authors, in particular in lesser known cases. Certainly, the best known and most recognized case is that of the steam engine which, thanks to the study of Rosenberg & Trajtenberg (2004) and Craft (2004), is among the most studied and recognized. But also, Lipsey, Carlaw and Bekar (2005), tried to better group the GPTs by defining them on the basis of their contribution to other sectors and to the economy itself.
However, what emerges from these studies is that the GPTs seen and studied so far can be traced back to the end of the twentieth century and the beginning of the twenty-first. The following space will therefore be dedicated to the hypothesis for some authors and conviction for others, who see Artificial Intelligence, and more particularly Machine Learning, establish itself as the most recent GPT. In fact, AI is potentially pervasive, it can improve over time and generate complementary innovations, always satisfying what is expressed

by Bresnahan and Trajtenberg (1995). AI is made up of clumping and complex interrelationships between its components (Hogendorn & Frischmann, 2020) and, moreover, as seen generically for GPTs, a delay on its implementation is expected, to then obtain a significant impact on growth as the previous GPTs (Brynjolfsson, Rock & Syverson 2017; Cockburn, Henderson & Stem 2018; Aghion, Jones & Jones 2017; Agrawal, McHale & Oettl 2018; Trajtenberg 2018). But, as biotechnologies and nanotechnologies, although considered GPTs, they are not yet fully developed and the proliferation of their uses is only in its infancy, making it difficult to study future developments (Shimizu, 2019). Current technological development, therefore, allows us to define notions on the effects of transformation even if at the current stage the productivity levels are not clearly influenced, which is reflected in the current state of the economy (Brynjolfsson, Rock & Syverson, 2017). Goldfarb, Taska and Teodoridis (2019), affirm that Machine Learning, which some let fall within the AI and others as an additional GPT, also responds to all the defining characteristics illustrated above and that only one aspect purely temporal, it will be able to define an application as a GPT or as an investment in an innovative sector for companies with high transformative potential. According to Brynjolfsson and McAfee (2017), Artificial Intelligence and Machine Learning not only represent the latest discovery in terms of GPT but also seem to be the most important for our era, becoming as stated by Trajtenberg (2018), “the next big thing”. This statement derives from the fact that, unlike other GPTs, AI together with ML allow innovation in many applications and are considered "invention of a method of invention", which suggests the importance of such a development of technology and the potential and economic impact greater than the development of each individual product (Cockburn, Henderson & Stem, 2018, citing Griliches, 1957). As described by Agrawal, Gans and Goldfarb (2017, cited by Brynjolfsson, Rock & Syverson, 2017), the current state of the art in generating Machine Learning systems is optimally configured to be able to increase or automate activities that involve at least some aspects of forecasting defined, managing to cover the most disparate areas of application, becoming pervasive and in some cases indispensable in carrying out tasks previously carried out by man. Describing ML, Brynjolfsson and McAfee (2017), indicate that the ability to automatically learn and perform tasks for which it is intended allows the system to learn to perform tasks autonomously. However, there are two aspects to consider: firstly, we as human beings have more knowledge than we can communicate and it is difficult to assign a precise definition to some sensations, nowadays ML allows us to define part of these perceptions to which we do not know how to give verbal feedback. Second, ML systems can be regarded as excellent students, high performance in different application ranges that are used throughout the economy to achieve a profound impact. Also, Brynjolfsson and McAfee (2017), continuing their analysis of AI as GPT, affirm that although it is used by thousands of companies around the world, most of the resulting opportunities have not yet been exploited. The applicability of Machine Learning moves in different economic sectors but currently the difficulty affects management, implementation and corporate imagination. Therefore, the development and diffusion of these new technologies, resulting from the incentives and obstacles that can shape their development, are a topic of considerable importance for economic research and the understanding of the conditions under which different potential innovators are able to access these tools and use them professionally (Cockburn, Henderson & Stem, 2018). While AI has profound implications for the economy and society in general, it has the potential to change the innovation process itself, with consequences that can be equally profound and that, over time, can dominate the direct effect (Cockburn, Henderson & Stem, 2018).

Recent advances in AI have affected multiple industries, which have focused on automated learning processes (Agrawal, McHale & Oettl, 2018). While historically speaking, AI has based its study of obtaining superhuman performance on a wide range of human cognitive abilities in a problem-solving approach, currently, scientific progress has been directed towards innovations that require a certain level of human planning and that applies to a narrow domain of problem-solving. The possible future is given by further discoveries that lead AI to significantly mimic the nature of human intelligence and subjective emotions in the field of Deep Learning. The field of MA is therefore configured, based on interpretations, as the development of AI or as a possible and future GPT that is reflected in the classic canons of Bresnahan and Trajtenberg (1995) (Cockburn, Henderson & Stem, 2018). The Table 2.2, proposed by Cockburn, Henderson and Stem (2018, p.14), is intended to be a representation of the distinction thought of AI and Machine Learning in the form of Deep Learning.

Table 2.2: Deep Learning in relation to GPT and IMI.

		General Purpose Technology	
		No	**Yes**
Invention of a Method of Invention	**No**	Industrial Robots	“Sense & React” Robots
	Yes	Statically coded Algorithmic Tools	**Deep Learning**

The current use of Deep Learning is implemented in the specific field, thus omitting the first point of the definition of Bresnahan and Trajtenberg (1995). But if the advances are widely applied in the perspective of "invention as a method of invention", profound learning of the machine will be highlighted, which will lead to very significant long-term economic, social

and technological consequences. The rarity of an event such as the arrival of Deep Learning could have a profound impact on economic growth and society. On the other hand, its effective implementation will need to develop institutions and a political environment that is conducive to improving innovation through this approach and doing so in a way that promotes competition and social well-being (Cockburn, Henderson & Stem, 2018). According to Aghion, Jones and Jones (2018), AI is configured as an input for the production of ideas that could be able to generate exponential growth even without an increase in the number of ideas generated by human beings, taking up what is stated by (Bloom et al., 2017), that scientific ideas may be harder to find. At present, however, in the ML field, supervised systems are used more, which deviate from the human capacity for unsupervised learning, but which are easier to develop and manage. The challenge is to fully encourage Machine Learning (Brynjolfsson & McAfee, 2017). Furman and Seamans (2018) observe how, despite on the one hand the economic literature associates innovation and economic growth and, on the other hand, AI is uniquely considered as a full-fledged GPT, there is still no corresponding gain on productivity. In response, Brynjolfsson, Rock and Syverson (2017), estimate a lag between technological progress and the commercialization of innovative new ideas based on progress and often based on complementary investments. In particular, this phenomenon affects the GPTs. In addition, Gordon (2014) defines that while innovations rely on Moore's Law,[4] there is no such improvement in productivity. In addition, Bloom et al. (2017), in a supplement to what has been stated on the difficulty of finding new scientific ideas, perceive that there is a greater need for wider research inputs to produce further productivity outputs. The very nature of AI as a GPT seems to explain the stagnation of growth despite the rapidity of technological advances it will therefore be the task of companies to reorganize operations, address the skills shortage within the education system and develop adequate digital and regulatory infrastructures to supporting AI-driven economic growth and creating added value (Klinger, Mateos-Garcia & Stathoulopoulos, 2018; Brynjolfsson, Rock & Syverson, 2017). Of another opinion are Agrawal, McHale and Oettl (2018), who see in the idea of AI capable of creating ideas, the potential way out of the current period of slowdown in productivity growth. In fact, Brynjolfsson, Rock and Syverson (2017), argue the coexistence of these two aspects, innovation by AI and slowdown in productivity, deriving from a restructuring associated with transformative technologies, which in terms of GPT have enormous potential in a perspective of radical change.
The positivism resulting from recent AI developments also involves a wave of generalized

[4]Moore's Law states that we can expect the speed and capability of our computers to increase every couple of years, and we will pay less for them. www.investopedia.com

pessimism, the implementation of such technologies tends to create situations in which there are winners and losers concurrently through widespread economic hardships (Trajtenberg, 2018). On the one hand, destruction of skills towards a sector can be observed, leading to a negative shock, but on the other, new windows of opportunity are opening up to be able to enter new sectors that are being defined. At the beginning of the life cycle of a new technological opportunity, therefore, experimentation takes place, given by the uncertainty about the technology and the search for the ability to obtain success (Scott & Storper, 2003 cited by Klinger, Mateos-Garcia & Stathoulopoulos, 2018). From the point of view of machinery, the process of replacing mechanization at the expense of human labour implies that automation exerts a displacement effect from machines in sectors where machines have a differential advantage (Acemoglu & Restrepo, 2018). But there is the presence of a compensation deriving from the increase in labour demand towards inefficient and secondary activities given that the main activity has increased its efficiency and automation by making new resources available (Panch, Szolovits & Atun, 2018). Furthermore, at present, AI represents a too small component of the global economy to have a significant impact on the labour markets but in the future, it could implement changes (Furman & Seamans, 2018).

The possibility of progressive automatic learning by AI still assumes speculative aspects regarding general and Artificial Intelligence. A change of this magnitude and rapidity assumes an unlikely reliance on the history of General Purpose Technology as a useful guide to addressing the impact of Artificial Intelligence. The experience gained in this field, however, should be of help in combining with other advances towards GPT to understand its dynamics and maximize its results (Agrawal, McHale & Oettl, 2018). A look at the past could portend the expectation of extraordinary growth, but that will not necessarily have repercussions even today. However, AI would seem to relate to the typical example of slow productivity growth followed by an acceleration, demonstrating how a GPT, which drives productivity growth, can reach multiple waves (Brynjolfsson, Rock & Syverson, 2017). While used by thousands of companies around the world, great opportunities still lie ahead, but the moment an AI-based product outperforms a human performance-based product in a given task, it will allow for faster and more effective spread of this type of innovation (Brynjolfsson & McAfee, 2017).

2.5 Concrete Applications of AI

The perspectives just discussed seem to portend how Artificial Intelligence will become part of everyday life as much as the internet or social media in the past. Personal life will be substantially impacted, and business decisions will be modified in relation to how decisions are made and interactions with external stakeholders. The perspective that is outlined does not concern whether AI will play a role in these elements but how it will play it and how it will coexist alongside the human being interacting. The problem that arises is which decisions the software will have to make, and which ones will still fall on the human being (Haenlein & Kaplan, 2019).
As seen above, at present, a delay in the application of the AI is expected, which will subsequently entail a strong impact on growth that has already occurred for the other GPTs (Brynjolfsson, Rock & Syverson 2017; Cockburn, Henderson & Stem 2018; Aghion, Jones & Jones 2017; Agrawal, McHale & Oettl 2018; Trajtenberg 2018). What, however, wants to be the element of an analysis of this section is that there are current applications that are being developed and that currently, in a more veiled and less marked way, are already part of people's daily lives or in any case are taking place gradually and gradually progressive (Mantovani, 2016; Gianni, 2020) Although the application of AI has various uses, six products that have Artificial Intelligence and that are part of the questionnaire that will be analysed in the next chapter will be examined below. The choice fell on commonly used products that were more recognizable by the interviewees.

2.5.1 Self-Driving Vehicles

Automatic driving support systems are defined as those technologies that collect data on the performance of the vehicle and the space-time context of its circulation, informing the driver and even making suggestions to the same or even taking partial control and, in an evolutionary way, the total of the vehicle (Gaeta, 2018). Autonomous vehicles scan the environment with techniques such as radar, lidar, GNSS, and artificial vision.[5] Advanced control systems interpret the information received to identify appropriate routes, obstacles and relevant signs (Lassa, 2012; European Parliament, 2019). Among these, the ADAS (Advanced Driver Assistance Systems) are the most appreciable, as their use leads to a

[5] All the systems mentioned allow the detection of the vehicle in its movement space. Subsequently, the decisions and actions to be taken are re-elaborated accordingly.

significant decrease in human involvement (Gaeta, 2018). Further developments make it possible to move different destinations without the need for human intervention, on roads that have not been pre-adapted (Torchiani, 2019).
In recent years, electronic means of driving support have developed rapidly. The main reason is the progressive improvement of road safety, given that more than ninety-five per cent of accidents are attributed to human error. The increase in on-board vehicle technology, and even more the production of fully autonomous vehicles, would seem to move towards a reduction in the rate of road accidents (Gaeta, 2018; European Parliament, 2019). From an economic and mobility point of view, digital technologies can also reduce traffic jams and pollution and improve access to mobility, for example by allowing the elderly and people with disabilities or reduced mobility to access road transport. Time savings in traffic that allows you to reach your destination more quickly while consuming less fuel (Gaeta, 2018; European Parliament, 2019). The efficiency of driving dynamics, in fact, could considerably reduce pollution, mainly of the atmospheric type but also the acoustic type (Gaeta, 2018). Furthermore, the self-driving vehicle market is expected to grow exponentially, thus leading to the creation of new jobs and the achievement by 2025 of profits of € 620 billion for the automotive sector and € 180 billion for the electronics sector. (European Parliament, 2019).
In particular, the ML algorithms developed for the automotive industry "train" to identify particular patterns within a corpus of information and, using statistical methods, progressively improve their performance. Automatic driving, of course, is no exception and several studies have verified the ability to learn and improve through the mistakes made (Iannaccone, 2019).
One of the biggest difficulties that developers face is to be able to predict all the possible variables that can be found on a road and to program an adequate reaction (which is usually entrusted to the driver's instinct). The software behind self-driving vehicles must therefore be able to perceive the surrounding environment, must determine the exact position on the road and must decide how to behave in a given situation. Perception, in essence, is ensured by the combination of data from the various sensors of the vehicle, such as radar and cameras. The real-time position is obviously ensured by the presence on the software of ultra-detailed maps, which allow the car to establish its position at the level of centimetres (Torchiani, 2019).
In 2014, SAE International[6] drew up an international standard in order to define, in 6

[6]SAE International (SAE) is a standardization legal personality in the aerospace, automotive and automotive industries.

levels, the different types of autonomous driving, based on the amount of intervention by the driver. They are composed as follows:

- **Level 0** - No autonomy: The driver has to deal with every aspect of driving, without any type of electronic support.
- **Level 1** - Driving assistance: The driver must take care of every aspect of driving but is supported at an informative level (in the form of visual or acoustic alerts) by electronic systems that can indicate the presence of dangerous situations or adverse conditions. At this level, the car is limited to analysing and representing situations, but the driver has total and full responsibility for driving.
- **Level 2** - Partial automation: The driver takes care of the driving, but there is a first driving integration. At this level, the car intervenes on acceleration and braking through safety systems, such as assisted braking, emergency anti-collision braking. The direction and traffic control remain under the control of the driver, although the steering can be managed in a partially automated way in certain scenarios with clearly visible road markings (systems called Lane Keeping Assist and, in the most complete versions, Traffic Jam Assist, Autosteer, Highway Assist, Driver Assist depending on the car brand).
- **Level 3** - Conditional automation: the car is able to manage driving in ordinary environmental conditions, managing acceleration, braking and direction, while the driver intervenes in problematic situations in the event of a system request or if he himself verifies adverse conditions.
- **Level 4** - High automation: The automatic system is able to handle any eventuality, but it must not be activated in extreme driving conditions such as in bad weather.
- **Level 5** - Complete automation.

In Europe, levels 1 and 2 are currently commercially available, while phases 3 and 4 are being tested in order to enter the market between 2020 and 2030. Fully self-driving vehicles (level 5) should be ready for 2030. By 2022, all new cars will have to be equipped with a connection (European Parliament, 2019). In level 5 cars, machine learning and automatic learning algorithms will allow to make the best possible choice in case of unexpected events of any kind. The level of safety is destined in the coming years to be further enhanced by the development of increasingly sophisticated vehicle-to-vehicle communications, which will allow the exchange of information and data in such a way as to prevent collisions. Further developments will affect the sensors used by the vehicles that will, in fact, communicate in real time with those incorporated in the road signs, in the traffic lights and the carriageways themselves (Torchiani, 2019).

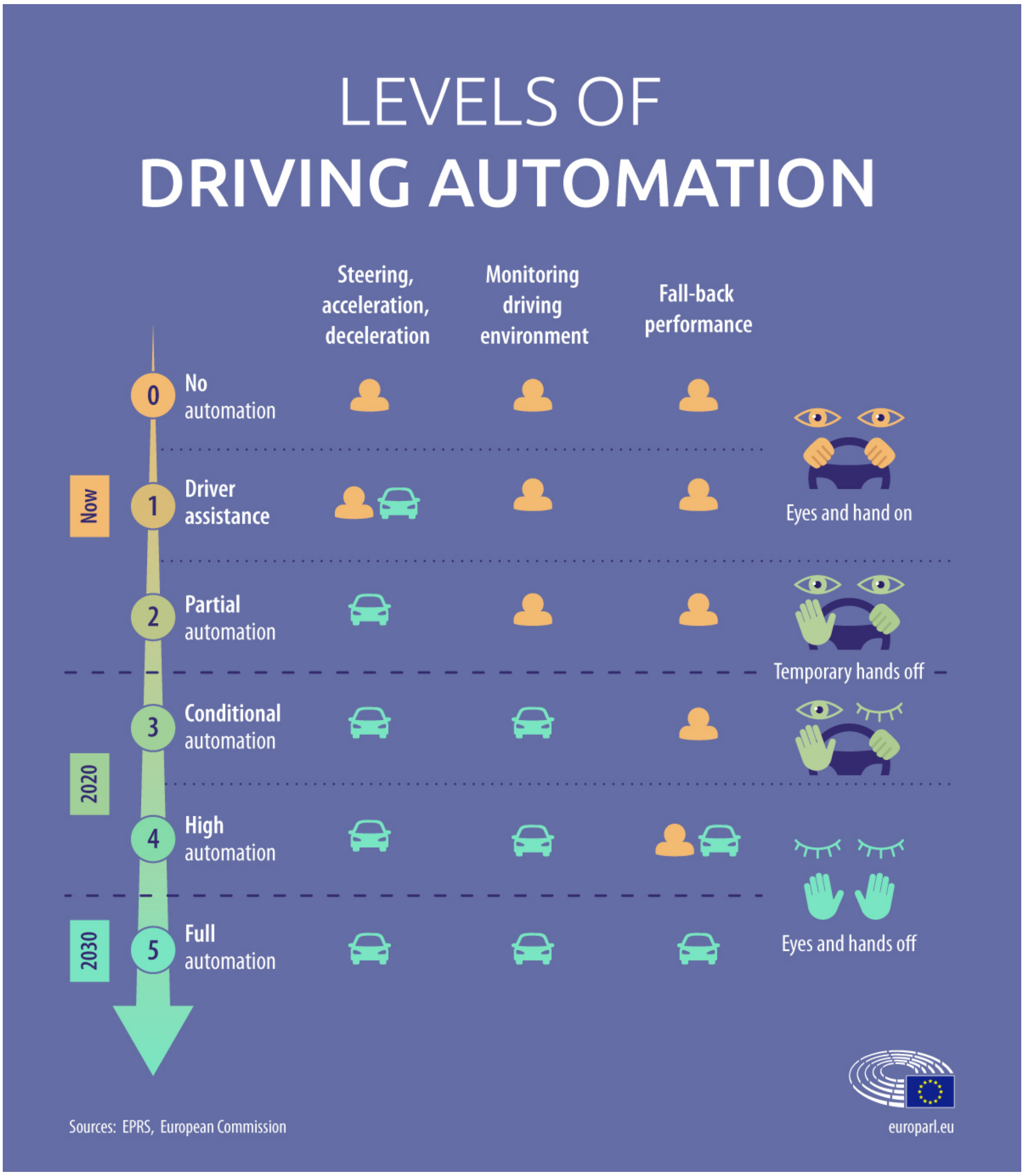

Figure 2.1: Driving automation levels. www.europarl.europa.eu

2.5.2 Smartwatch

A smartwatch is a watch with other functions beyond simple timing being a computer for general use, connected to the network with a series of sensors to be worn on the wrist (Rawassizadeh, Price & Petre, 2014). The presence of detection tools could give the impression that these are sensors, hardware, communication middleware, network and data, but the real value is given by the data processing by Artificial Intelligence (Amyx, 2014). Smartwatches differ according to the type of data collected and as defined by Jin (2019) are divided as follows:

- Sports data, such as acceleration, rotational speed, running steps, etc.
- Physiological data such as heart rate information, blood pressure, body temperature, blood volume, sound pressure, skin temperature, skin conductance, emotional state, sleep quality, fatigue state, general health state, alcohol intake or caffeine, etc.
- Environmental data such as coordinates of the global positioning system, magnetic field strength and ambient light flux, etc.
- Communication data such as call information, SMS information, screen pressure and conditions of use of electronic products, etc.

The Artificial Intelligence of wearables currently allows the collection of data on rapid body movements, falls or unexpected events in order to develop intervention strategies in situations of need. In the sports field, it is traced back to the classification of activity, positioning and navigation, analysis of family behaviour, gait analysis and recognition of gestures and habits. The software aims to avoid excessive exercise and even heart attacks. Additionally, it can detect whether the user has reached an appropriate exercise plan and is suitable for long-term exercise users. In the health sector, on the other hand, the physiological data of the human body are collected by intelligent electronic devices that are integrated or that come into direct contact with the body. The results obtained can be used to judge physical condition, health monitoring, chronic disease management and disease prevention for the elderly, monitoring the abnormal conditions of patients with heart disease, and detect early signs of disease. Another important aspect is physical and psychological data, such as mood, sleep quality, fatigue, general health and alcohol or caffeine intake. Information on user communications is also processed through the use of electronic products. This favours a yardstick for judging users' psychological stress (Jin, 2019).

The area that covers the greatest current interest in smartwatches is made to fall on the health level because it is based on the characteristics defined by Reeder and David (2016):

- They are familiar to most people;
- They are increasingly available as a consumer device;
- Enable continuous monitoring of physical activity and physiological measurements in near real time;
- Support customized messages and reminders;
- Enable communication between patients, family members and healthcare professionals;
- Enable on-site, mini-surveys and behavioural verification based on sensor-based measurements.

An aspect that is outlined by what is proposed by Reeder & David (2016) is given by the fact that one wearable goes beyond the patient's self-reporting of a health disorder but is configured as a tool for prevention and timely intervention in situations of need.
Although Jin's (2019) study defines how the wearables category has been able to capitalize on AI, it has not yet fully developed its potential which needs further development and improvement. Reeder and David (2016), perceive that in comparison with laboratory data, the sensors of smartwatches, although reliable, need further development to improve their accuracy. However, some devices have already decided to improve their reading skills to offer a medical assessment to their user customers. While the reading may not be accurate, the data collected, in the environment in which a smartwatch usually operates, contain a lot of noise caused by the influence that surrounds it. Therefore, it is necessary to develop methodologies and products that know how to operate above the disturbance and that can cope with the different environmental characteristics in which they would find themselves operating. Furthermore, it is necessary to take into account the behaviours of the individual that may differ from each other leading to the need to configure a highly customized product based on the data collected and processed (Jin, 2019).

2.5.3 Home Automation

Home automation is a science born with the third industrial revolution and deals with the study and application of technologies to improve home life through user-programmed

or partially autonomous systems (Petrellese, 2017). The term home automation is part of the common language and in the imagination is traced back to the switching on and off of switches and timers. However, further developments have led it to occupy the field of interaction, where different devices interface in a modern communication infrastructure called a home network. Modern home automation is therefore the fusion of the concepts of home automation itself, telematics and communication (Soucek, Russ & Tamarit, 2000).
AI offers an added value to the known definition of smart home; simple commands can be transformed into integrated environments in which the Artificial Intelligence mechanism can deduce and react appropriately based on changing conditions and events. The inputs generated will be obtained from multiple sensors present in multiple products which, through centralized management, will interact with the events that occur in the environment in which they operate (Bregman, 2010; Guo et al., 2019). In these systems, AI plays the role of knowledge and rules database, decision maker, action implementer and appliance controller (Kumar & Qadeer, 2012). According to Guo et al. (2019), AI operates in the home automation sector, recognizing human activity, through six clusters defined as follows: activity recognition, data processing, speech recognition, image recognition, process decision making and forecasting. The authors also define these clusters in fact data processing allows the extraction of information from different sources by analysing the intrinsic relationships. The voice recognition technology allows interactions with the only use of the voice to give commands. Through image recognition, facial recognition, emotion recognition, biometrics and scene understanding can be achieved. Finally, artificial intelligence plays the role of the one who makes decisions. It can decide what action needs to be taken in response to the input data (Kumar & Qadeer, 2012; Guo et al., 2019).

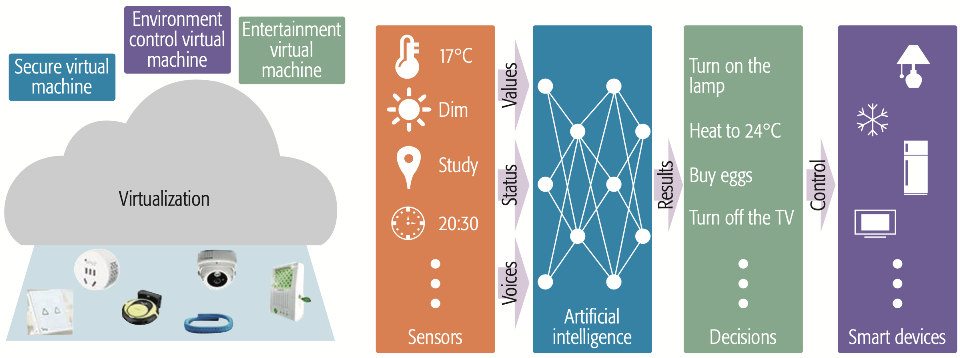

Figure 2.2: Artificial Intelligence through home automation (Xu et al., 2016, p. 121).

As seen, inside the house, different sensors are incorporated capable of generating data

based on the routine of its occupants, following processing by an intelligent agent, which will allow generating useful knowledge such as models, forecasts and trends. Concerning the information obtained, a smart home can select and automate actions to achieve the goals of the smart home application (Orpwood, 2012).
Among the advantages of a smart home, certainly the first is to make the life of its occupants more comfortable. Secondly, control on a home automation site has the ability to offer security and tranquillity, ensuring interactions with the environment and its systems at any time and ensuring help in emergencies. From an economic point of view, the analysis of consumer behaviour and habits makes it possible to predict and optimize consumption deriving from the users of the home, creating an optimized yield towards performance when needed. The quality of life of elderly and disabled people is improved through support in daily activities and help and collaboration based on lifestyle habits (Robles & Kim, 2010; Guo et al., 2019). However, some perplexities accompany Artificial Intelligence, due to their system complexity and integration of the different devices, the different areas of control and supervision, the different information technologies and the learning mechanisms and reasoning skills used in updating of the information system, all the actors who correspond to developers, suppliers and users must cooperate with each other. In addition to the actors themselves, the devices and systems must be compatible with common standards that place their bases on commonly used and universally recognized models (Bregman, 2010). But, in order to cooperate, people need a line of dialogue of customer information to the developer through suppliers in an anonymous way. This flow of information, including also anomalous events actually verified and in which the system has placed its intervention, allows a progressive improvement of the system through Machine Learning. The greater the number of cases and data collected, the greater and faster will be the updates and improvements of the AI interfaced with home automation (Bregman, 2010).

2.5.4 Virtual Assistants

One of the objectives in which AI is found to operate more often is the natural dialogue between man and machine in fact voice assistants are software agents that can interpret human speech and respond via synthesized voices (Hoy, 2018). These interaction systems represent the area in which the fastest growth in Artificial Intelligence is taking place (Këpuska & Bohouta, 2018). The technology in this field uses Natural Language Processing (NLP) which, commonly through textual data, through computational methods, make an analysis of linguistic data creating within the machine the ability to understand and deepen

linguistics. By doing so, the software is able to provide human-computer interaction to store initial information, solve specific problems and perform repetitive tasks requested by the user (Verspoor & Cohen, 2013 cited by Goksel-Canbek & Mutlu, 2016; Goksel-Canbek & Mutlu, 2016). Hauswald et al. (2015) define a virtual assistant as an application that uses inputs such as the user's voice, vision and contextual information to provide the user with assistance. Your answers will then be communicated in a natural way through the use of language, making recommendations and performing actions.
According to Minker and Néel (2002), voice communication represents the intermediary between man and machine:

- In some environments, the voice is the only method of communication and is able to assist disabled and blind people.

- The voice is more efficient than typing on a keyboard, in the first case it is possible to reach 200 words per minute, while with the help of the keyboard it is possible to reach an average of 60 words per minute. The vocal reading approach is natural and requires less effort (reading a text can reach up to 700 words per minute).

These systems are currently incorporated into smartphones, smart TVs and vehicle infotainment systems (Chen, Celikyilmaz & Hakkani-Tur, 2017). Furthermore, in addition to consumer use, they can represent an option, thanks to the range of applications, for companies, education, government, healthcare and entertainment (McTear, 2016 cited by Këpuska & Bohouta, 2018). The estimate by CHM Research (2016) also predicts how, before 2030, millions of people will interface with the use of their voice to interact with the machine and the services that are already part of their daily life today (Këpuska & Bohouta, 2018). Virtual assistants allow, through automation, to save time by executing commands while the user is engaged in other activities. They, therefore, allow you to plan daily activities by making work and free time efficient (Wajcman, 2019). Furthermore, as stated in 2014 by theoretical physicist Stephen Hawking, virtual assistants as currently known (Siri, Google Now and Cortana) represent the greatest products of human intelligence created in human history and, despite some disadvantages and costs of accomplishments, have a high potential where research should focus. However, there are also several issues with currently available voice assistant products. In particular, privacy and security controls will need to be improved before voice assistants can be used for anything that requires confidentiality (Hoy, 2018).

2.5.5 Chatbot

Chatbots are an emerging category of products with Artificial Intelligence already used by millions of people thanks to the ease of developers to access natural language services (Yanet al., 2016).
A chatbot can be defined with an AI-based program capable of simulating human conversations, once the request has been processed, the bot provides a series of timely and relevant responses. Thus a "non-human" contact takes place that uses Artificial Intelligence algorithms to return a structured dialogue to the end user (Torchiani, 2018a). Their work takes place as a result of analysis and identification, extracting the entities relevant to the resolution of the problem, and subsequently providing the user with an appropriate response. Chatbots are able to operate through three classification methods: pattern matching, through the grouping of the text into patterns, the Natural Language Understanding (NLU), which represents the ability of a chatbot to transform the text into data capable of to be understood by the machine, and Natural Language Processing (NLP), which is the ability to transform the text introduced into structured data that allow a subsequent selection of the suitable answer (Patel, 2020). Being able to understand what a customer is asking for, or what their problem is, chatbots are used as automated systems to manage customer support chats (Mantovani, 2016). According to Patel (2020), they are divided into two types:

1. **Rule based chatbos**: which represent chatbots that follow a predefined path during conversations and where the user himself must select explicit options that will involve the next step of the conversation;

2. **Conversational chatbots**: which represent chatbots with an assistance function. They are interactive and personalized and converse with users in the same way that humans interact and communicate in real life situations.

Moreover, Patel (2020) also analyses the positive aspects of using a chatbot, improving operational efficiency, creating savings for companies and offering convenience and additional services to customers by solving their problems without any human intervention. According to the author, the improvements are as follows:

- **Reduction of waiting times**: for 21% of consumers the chatbot is the easiest way to contact a company and to get a quick response without long waits.

- **They can work 24 hours a day, 7 days a week**: being based on information technology, they are available at any time of the day, guaranteeing assistance at all times.

- **Easy scalability with bots**: even during peak working hours, the system manages all requests without additional costs for each additional employee.
- **Reduction of customer service costs**: once the initial cost for the system has been incurred, it operates independently.
- **Build customer loyalty**: thanks to the involvement the percentages of abandonment are reduced.

According to Maci (2016), it raises the question of whether, at present, chatbots are able to truly satisfy any real user need. Some users would seem less inclined in case of a real need to want to interface with a chatbot but would prefer more human contact. Signorelli (2017), states that for some customers the chatbot is difficult to use and has a poor level of customization and that chatbots are limited to their programmed level of knowledge, limiting their ability to respond, still involving human intervention.

2.5.6 Augmented Reality (AR)

Augmented reality represents processing carried out by a computer through sensors and algorithms to determine the position and orientation of a camera. AR technology, through a computer, create objects in 3D graphics and orients them as they would appear from the camera point of view, finally superimposing the generated images on those of the real world (Torchiani, 2018b). It, therefore, represents a direct or indirect live view of a real physical environment, the elements of which are augmented by computer-generated sensory input such as sound, video, graphics or GPS data (Tritium, 2020). In essence, therefore, augmented reality transforms huge masses of data and analytics into images or animations that are superimposed on the real world. Combined with IoT data, AR applications are leading numerous companies to completely redefine the way they design, manufacture, sell, manage and support products (Torchiani, 2018b). Costa (2019) states, based on an article in the Harvard Business Review, that augmented reality is able to eliminate the dependence on decontextualized and difficult to process two-dimensional information on the pages on the screens, improving the ability to understand and apply information in the real world. In fact, 80-90% of the information received by human beings passes through vision.

Torchiani (2018b) defines how augmented reality works by starting it from a device equipped with a video camera (smartphone, tablet or smart glass) on which AR software has been loaded. When the user points the device and looks at an object, the software recognizes it through a computerized vision technology, which analyses the flow of images. AR information is presented in a three-dimensional experience superimposed on the object rather than on a two-dimensional page that appears on a screen. What the user sees, therefore, is partly real and partly digital. A basic principle of augmented reality, in fact, is that of the overlay: the camera reads the object in the frame, the system recognizes it and activates a new level of communication that overlaps and integrates perfectly with reality, enhancing the quantity. of detail data in relation to that object. Costa (2019) sees augmented reality is, in fact, a form of visual content management 2.0 that allows companies and organizations to engage customers through innovative ways of expressing themselves: in fact, it adds new levels of information, in real time and with a high rate of interaction using mobile devices of any kind, including wearable technologies, creating new and broader customer experience strategies.

Furthermore, Trizio (2020) defines some areas of application of augmented reality that are already exploited. They range from Gaming, where perhaps the best known example is the famous Pokémon GO, teaching and learning, thanks to the interactive involvement of students, marketing and e-commerce, thanks to simulations and virtual fitting rooms, healthcare, which allows you to view clinical data of patients in 3D, facilitating reading and the military environment, through exercises through a viewer.

However, some negative aspects surround augmented reality. From a health point of view, many users have complained of symptoms such as nausea and headaches related to the use of this type of technology. In reality, there are no scientific studies on the subject, given the substantial novelty of these technologies which prevents investigating the long-term consequences. Some manufacturers of viewers, in their warnings, have advised against their use by categories such as pregnant women and children, probably for precautionary purposes (Costa, 2019).

But in addition to some negative aspects, the prospects appear positive. According to a research carried out by Capgemini of about 700 executives in the automotive, manufacturing and utility sectors. The widespread excellent is reinforced by some percentages: 82% of companies currently implementing these solutions believe that the benefits are exceeding their expectations, while a good 46% of respondents expect AR and VR to become mainstream within the next three years, while a further 38% expect this change within the next three to five years. In general, augmented reality is considered to be more applicable in the company, precisely because of its ability to interact with reality, but also some virtual reality solutions are believed to be able to positively impact the company business.

Chapter 3

Consumer Perspective Analysis

3.1 Introduction

As noted in the previous chapter, Artificial Intelligence plays an important role in its position as the new General Purpose Technology for its current and future applications. Governments and organizations are therefore preparing to face these challenges that will lead AI to become increasingly widespread and commonly used (Dwivedi et al., 2019). The current permeation in society is evident, and concepts such as AI, robots and automation are not interchangeable notions. The machines have been used inside factories for a long time, through repetitive tasks in an efficient manner. But the concept of automation differs from that of AI where the system understands data rather than being limited to its collection (Evans 2017, cited by Carriço, 2018). In fact, currently, the use of products with AI is increasing due to the simple fact that, by their nature, they can make autonomous and semi-autonomous decisions through interactions with the surrounding environment (González García et al., 2017).
The current developments that users are going against allow the facilitation or improvement of some functions that concern the consumer. This type of development has two sides of the same coin, on the one hand, it would lead to an increase in the well-being of the consumer by making their choices easier, practical and efficient and by implementing actions in their place, but on the other hand, they can create a feeling of alteration in the perception of consumers' autonomy, undermining their well-being (André et al., 2017). On this aspect, products equipped with Artificial Intelligence are considered as innovative products and therefore the behavioural intention aimed at their use can occur through the understanding of the previous research on the adoption by users of innovative products (Sohn

& Kwon, 2019). Technological adoptions are not implemented by consumers instantly, but the adoption times are distributed over time (Bass, 1980) and in particular, GPTs take a long time to be adopted and have an economic impact (David, 1989; Lipsey, Bekar & Carlaw, 1998). On the other hand, technological innovations involve a significant change in consumer habits and therefore lead to implications regarding the changing behaviour towards the adoption of new technology (Antioco & Kleijnen, 2010). In this regard, numerous scholars have established an association between the adoption of new technologies and perceptions regarding the ease of use and the perceived usefulness of new technology, creating models to support this analysis that are still used today. A correlation is therefore outlined between the basic usability of technology and the perception of the utility of the consumers users (Fishbein & Ajzen, 1975; Davis, 1989; Venkatesh, 2000; Venkatesh & Davis, 2000).

3.2 Theoretical Framework of Technological Acceptance

According to Groß (2015), most studies on innovative products are based on the Technology Acceptance Model (TAM), Theory of Planned Behaviour (TPB), and Unified Theory of Acceptance and Use of Technology (UTAUT).
As a model used for the questionnaire on Artificial Intelligence, that will be presented later, this section will therefore be dedicated to the TAM and its structure, the literary bases on which it is founded and the results that can be obtained.

3.2.1 Literature Review of Technological Acceptance

In the literature, various theoretical models have been developed that attempt to interpret the individual's attitude towards the use of technological products. In this context, everything originated from studies deriving from social psychology that led in 1975 Fishbein and Ajzen to formulate the Theory of Reasoned Action (TRA) (Muscarà & Messina, 2014) (Figure 3.1). The authors assume that the factors that determine the integration of the use of technologies in the behavioural repertoire of the individual are basically two: Attitude Toward Behaviour, which represents the set of feelings and attitudes (positive or negative) towards the possibility of putting into practice a certain behaviour and the subjective norm, or subjective perception of what significant others think about the implementation of a certain behaviour (Fishbein & Ajzen, 1975). In practice, a person's actual behaviour could be determined by considering their previous intention along with the person's beliefs about the given behaviour (Davis, 1985).

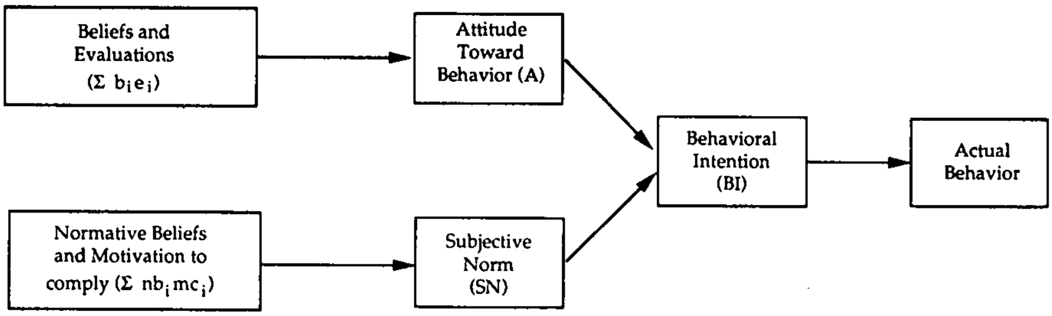

Figure 3.1: Theory of Reasoned Action (TRA) (Davis, Bagozzi, & Warshaw, 1989).

In its simplest composition, the model consists of the following formulation:

$$BI = (AB)W_1 + (SN)W_2$$

Where BI represents the behavioural intention, AB the attitude towards the execution of behaviour, W_1 and W_2 the empirically derived weights and SN the subjective norm relating to the execution of the behaviour (Hale, Householder & Greene, 2002).

Although the authors have developed the model from the point of view of healthy behaviour, such applications can be extended in any context of understanding and prediction of human behaviour, even of a technological nature (Fishbein & Ajzen, 1975; Muscarà & Messina, 2014).

In 1985 Ajzen extended what he saw in the TRA to the theory that takes the name of Theory of Planned Behaviour (TPB) involving the addition of a main predictive factor that is given by the control of perceived behaviour (Figure 3.2). It follows that with this evolution it is possible to take into account all the times in which people intend to conduct a behaviour, but this behaviour is hindered due to subjective and objective reasons. It follows that the two previous elements (attitude toward behaviour and subjective norm) join together behavioural intention favouring the attitude towards behaviour and subjective norm and the control of perceived behaviour (Ajzen, 1991).

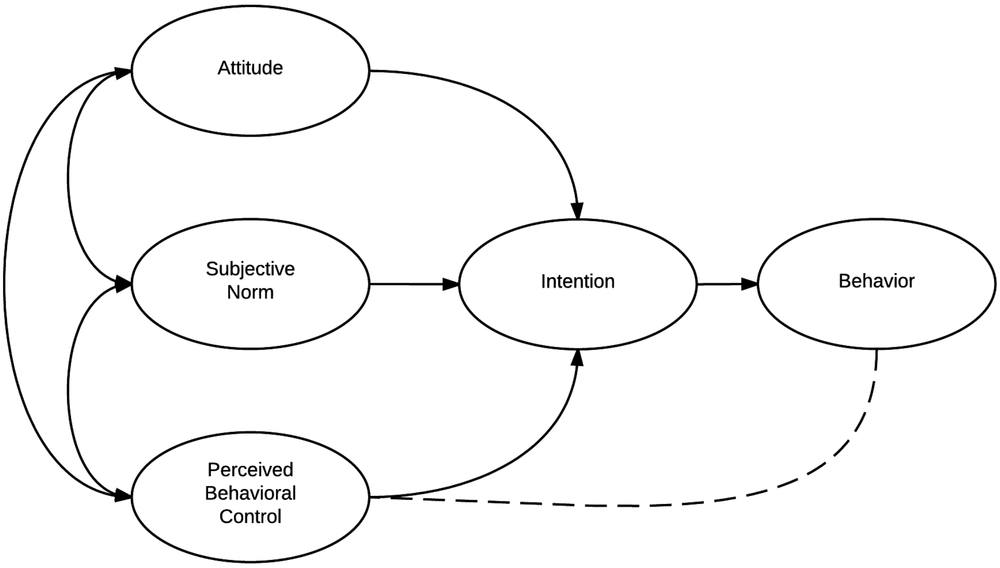

Figure 3.2: Theory of Planned Behaviour (TPB). https://upload.wikimedia.org/

3.2.2 The Technology Acceptance Model (TAM)

Introduced by Davis in 1986, the Technology Acceptance Model represents an adaptation of the previously seen TRA model that was specifically designed to model user acceptance of information systems. The TAM is structured to provide an explanation of the determinants of technological acceptance in a general way, managing to explain user behaviour (Davis, Bagozzi & Warshaw, 1989). Technology acceptance is then deferred to two technology acceptance measures replacing many of TRA's attitude measures.
Davis (1985), in his introductory work on TAM, proposed that the use of the system is a response that cannot be explained or predicted by the user's motivation, which, in turn, is strictly influenced by an external stimulus consisting of the characteristics and capabilities of the actual system (Figure 3.3).
Later, re-evaluating the aspects of the model, he defined the motivation of users with the definition of three factors: the Perceived Ease of Use (PEOU), the Perceived Usefulness (PU) and the Attitude Toward Using (A) where the attitude of use of a system is the major determinant of whether or not to use a system. It is influenced by the other two elements where, however, the Perceived Ease of Use has a direct influence on Perceived Usefulness (Davis, 1989). In fact, the author defines the Perceived Usefulness as "the degree to which a person believes that using a particular system would enhance his or her job

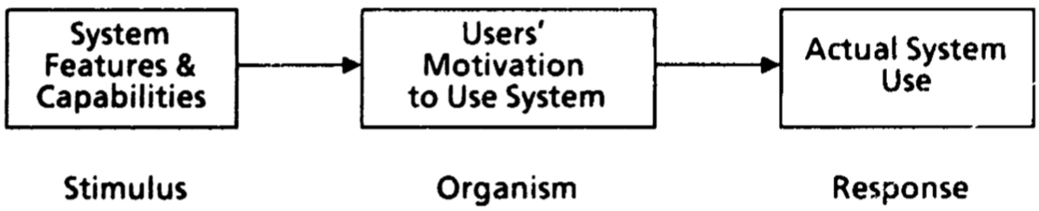

Figure 3.3: Conceptual model of technology acceptance (Davis, 1985).

performance" and the Perceived Ease of Us as "the degree to which a person believes that using a particular system would be free from effort "(Davis, 1989) (Figure 3.4).

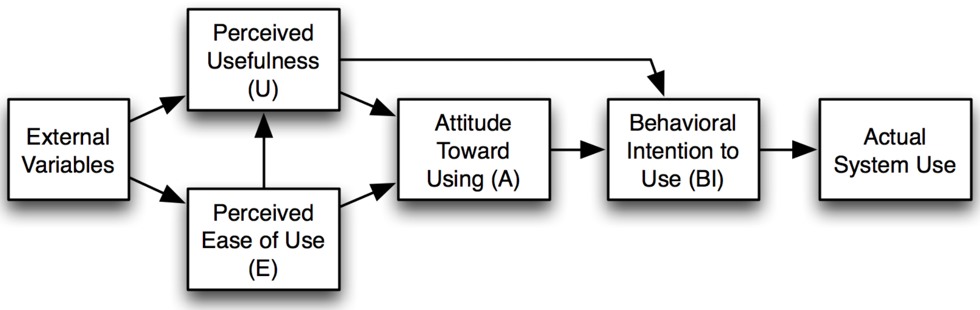

Figure 3.4: The original TAM model. https://upload.wikimedia.org/

Over time, numerous changes have been made to the original TAM model. The major and well-known improvements were implemented with the introduction of TAM 2 (Venkatesh & Davis 2000 & Venkatesh 2000) and with the Unified Theory of Acceptance and Use of Technology (Venkatesh et al. 2003). The system has been able to evolve thus becoming better known in the explanation and prediction of the use of the system. In fact, it is used in most research focused on technological acceptance (Lee, Kozar & Larsen, 2003).

3.3 Research Methodology

As just noted above, the TAM model represents the maximum expression in the field of technological acceptance (Lee, Kozar & Larsen, 2003). In the questionnaire described below, the original TAM model was used, that is the one conceived by Davis (1986) and then well defined by Davis, Bagozzi and Warshaw (1989).

On the basis of the theoretical framework previously discussed, a series of hypotheses have been formulated that will be subsequently verified through a SEM analysis (Figure 3.5):

- **H1**: The greater the perceived ease of use of a product with Artificial Intelligence, the greater the perceived usefulness of it.
- **H2**: The greater the perceived ease of use of a product with Artificial Intelligence, the more positive the attitude towards adopting this innovation.
- **H3**: The greater the perceived usefulness of a product with Artificial Intelligence, the more positive the attitude towards the adoption of this innovation.
- **H4**: The greater the perceived usefulness of a product with Artificial Intelligence, the more positive the consumer will behave towards the intention of adopting this innovation.
- **H5**: The attitude towards the act of adopting a product with Artificial Intelligence has a direct and positive effect on the behavioural intention of the consumer to adopt this innovation.

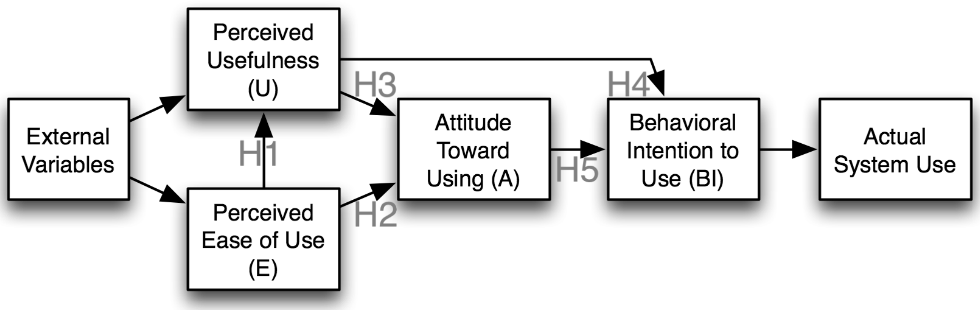

Figure 3.5: The original TAM model with references to the hypotheses adopted

3.4 Data Collection

The idea behind this study is to analyse the perception and intention of adopting products equipped with Artificial Intelligence and which are currently at the dawn of distribution and consumption on the market and are in the process of accessing them.
The questionnaire was conducted online through the use of Qualtrics statistical software

to empirically analyse the perceived usefulness, ease of use and interest accompanied by the propensity to use or purchase a product equipped with Artificial Intelligence. The will is, therefore, to be able to evaluate the technological acceptance of AI and in order not to make the compilation of the questionnaire too abstract, 6 categories of the most well-known products have been outlined in which AI is suitable for use and development. The 6 categories are: self-driving vehicles, smartwatches, home automation, virtual assistants, chatbots and augmented reality. To avoid respondents responding to products of which, despite a generic knowledge of the population, a filter was applied at the beginning of the questionnaire in which the degree of confidence in products equipped with AI was asked. In the event of a negative or partially positive response, a presentation page for each product was proposed in which an attempt was made to recreate a familiarity with the object.

Subsequently, all the participants were asked to select, by choice, only two of the six products in order to have two TAM forms compiled for each interviewee and which matched two products with different AI. Each request, apart from the initial configuration questions, did not include a mandatory answer, leaving the interviewee free to choose. The basic idea was to analyse the perception of AI in a practical way even for those who do not have extensive knowledge. The product range has recreated a wide range of applications to make the result more truthful. In this regard, all the data obtained are evaluated together in order to therefore be able to define a unified application towards AI. The data was collected by sharing the access link to the questionnaire by sending it to private chats and groups on the main messaging social networks. To expand the sample, the mailing list of the University of Aosta Valley was also used. In this case, most of the data obtained are represented by students and acquaintances who reflect the data from 18 to 30 years.

In the responses configured within the TAM model, the range was given through a 5-step Likert scale[1] where 5 = completely in agreement, 4 = fairly in agreement, 3 = neither in agreement nor in disagreement, 2 = fairly in disagreement and 1 = completely disagree.

Respondents were required to answer a number of 4 demographic questions, 2 questions for defining the choice of products and for assessing knowledge of AI and, for each product chosen, 4 macro-questions divided into 21 possible choices. The number of questionnaires obtained was 413, but once the completeness of the answers was verified, the value stood at 282, bringing the number of TAM models that will complete the analysis on Artificial Intelligence to 564.

[1]The Likert scale is a psychometric attitude measurement technique. This technique is distinguished mainly by the possibility of applying methods of analysis of the items based on the statistical properties of the measurement scales at intervals or ratios. https://it.wikipedia.org/

3.5 Demographic Statistics

The personal data that were collected through the questionnaire will be reported below (Table 3.1).

Table 3.1: Summary of demographic statistics (N=282).

Items	Frequency	Percentage
Gender		
Male	85	30.14
Female	197	69.86
Age		
18-30	224	79.43
31-40	23	8.16
41-50	10	3.55
51-60	21	7.45
61-70	4	1.42
70+	0	0.00
Education		
Primary/Junior High School	11	3.90
Professional Qualification	7	2.48
High School	152	53.90
Bachelor Degree	99	35.11
Master's Degree/PhD	13	4.61
Job		
Farmer	1	0.35
Artisan	0	0.00
Operative	4	1.42
Employee	38	13.48
Manager	2	0.71

Items	**Frequency**	**Percentage**
Business owner	8	2.84
Teacher	9	3.19
Freelance	23	8.16
Student	164	58.16
Retired	1	0.35
Unemployed	8	2.84
Other	24	8.51

The number of respondents were asked to define, following a brief definition, their knowledge of AI. The sample examined is divided between those who know the subject and those who do not have specific knowledge. Only a small part of the sample does not know the subject (Figure 3.6).

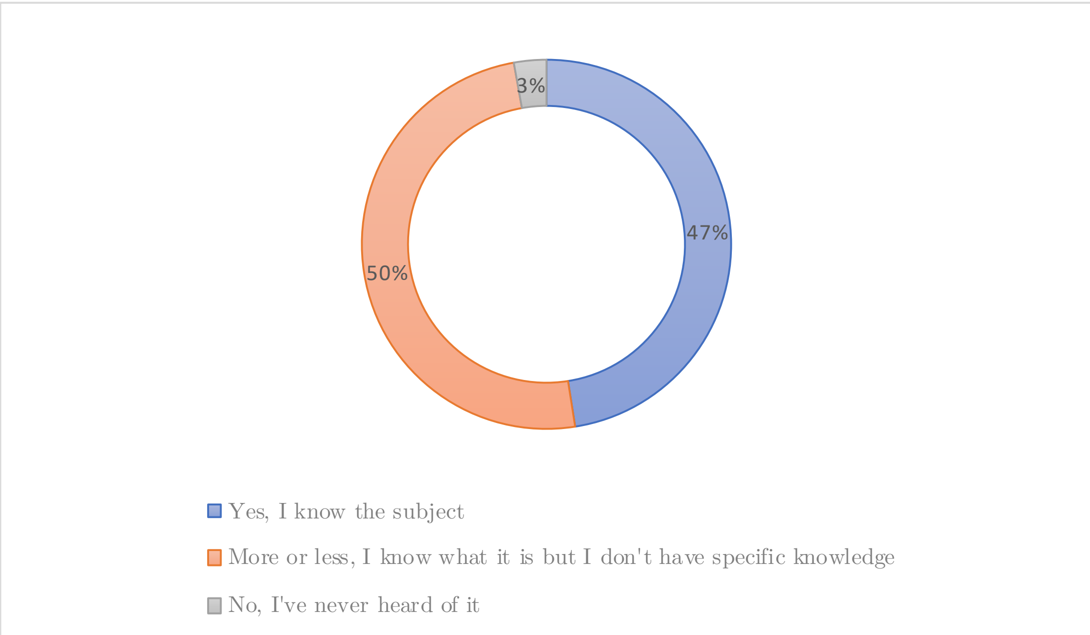

Figure 3.6: Knowledge of Artificial Intelligence.

In the following graph (Figure 3.7), it is instead possible to observe how self-driving vehicles and smartwatches and fitness trackers represent the main products towards which the interviewees have more information and/or arouse the greatest interest. Home automation and virtual assistants follow with as many interesting values.

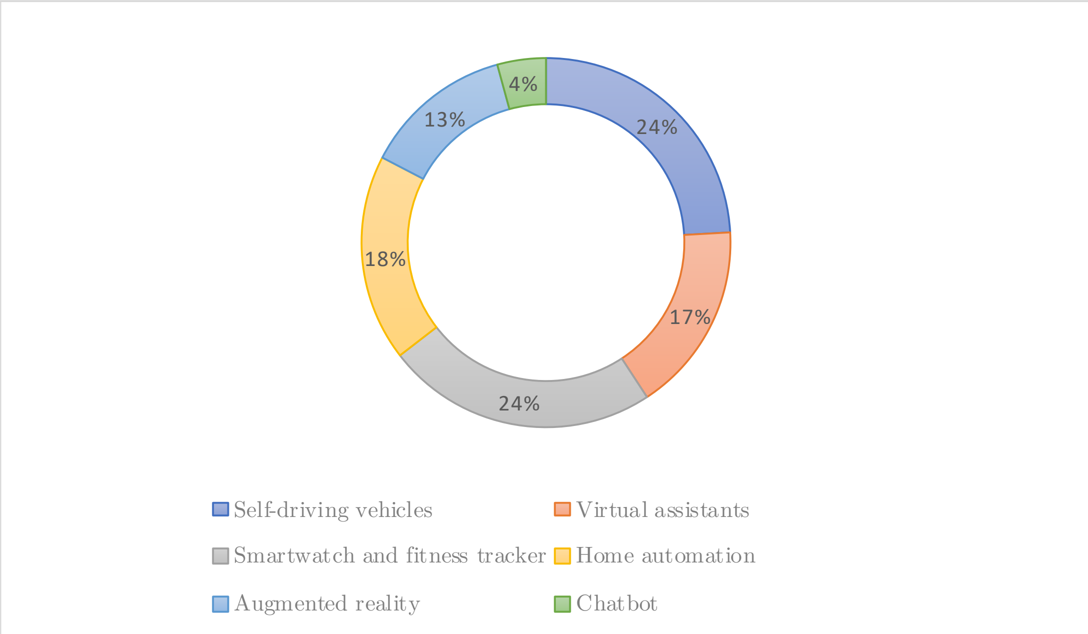

Figure 3.7: Classification of interest and knowledge of products with AI.

3.6 Findings

In order to validate the model, as previously introduced, Structural Equation Modeling (SEM) will be used, a second generation modeling technique also used with technology acceptance models (Bagozzi, Davis & Warshaw, 1992).
SEM can perhaps better be defined as a class of methodologies that seeks to represent hypotheses on summary statistics that derive from empirical measurements in terms of a smaller number of "structural" parameters defined by a hypothesized underlying model (Kaplan, 2009). The above differs from the first generation because it allows a single, systematic and complete analysis of a series of interrelated research questions by modeling the relationships between multiple independent and dependent constructs simultaneously (Gerbing & Anderson, 1988).
As follows, the 1989 Davis TAM model, applied to the responses obtained, was examined through Structural Equation Modeling (SEM).

3.6.1 The Measurement Model

Cronbach's alpha was used to assess the reliability of the constructs (Table 3.3).[2] The results obtained were highly positive with most of the values close to 0.9 and never lower than 0.79, always taking into account that values between 0.7 and 0.8 are considered acceptable and higher values are good or excellent (Tavakol & Dennick, 2011). The factor loading shows the variance explained by the variable on that particular factor (Table 3.2). In the SEM approach, as a rule of thumb, a factor load of 0.7 or greater indicates that the factor extracts a sufficient variance from that variable and these values are respected in almost the entire questionnaire.

Table 3.2: Results of the confirmatory factor analysis.

Construct	**Item**	**Factor Loading**
Perceived Usefulness		
	A *<selected product>* would help me save time	0.83
	A *<selected product>* would help me make less effort	0.62
	A *<selected product>* would help me be more productive	0.61
	A *<selected product>* would make me feel safer	0.52
	I think a *<selected product>* would prove very useful for me	0.57
Perceived Ease of Use		
	The use of a *<selected product>* would be easy	0.70
	I have the necessary knowledge to use a *<selected product>*	0.83

[2]Cronbach's alpha measures reliability or internal consistency and checks whether multi-question Likert scale surveys are reliable. https://www.statisticshowto.com/

Construct	**Item**	**Factor Loading**
	The interaction with a <*selected product*> would be clear and understandable	0.73
	I find it easy to get a <*selected product*> to do what I want	0.81
	I find the instructions for using a <*selected product*> clear and easy	0.74
	I would feel comfortable using a <*selected product*>, even with its more advanced features	0.76
Attitude Toward Using		
	Using a <*selected product*> in everyday life would be pleasant	0.72
	Using a <*selected product*> in everyday life would be effective	0.73
	Using a <*selected product*> in everyday life would be beneficial	0.81
	I would trust a <*selected product*> to achieve the intended goal	0.82
	I would prefer to use a <*selected product*> (if available) instead of a conventional product	0.81
Behavioral Intention		
	I intend to use a <*selected product*> in the future	0.50
	I intend to use a <*selected product*> frequently	0.87
	I am going to recommend a <*selected product*> to other people	0.84
	I intend to purchase a <*selected product*> in the future	0.90

Construct	Item	Factor Loading
	I intend to use a <*selected product*> in a sharing system with other people	0.87

Table 3.3: Internal consistency reliability (Cronbach's alpha).

Construct	**Cronbach's alpha**
Perceived Usefulness	0.79
Perceived Ease of Use	0.88
Attitude Toward Using	0.88
Behavioral Intention	0.89

3.6.2 The Structural Model of AI Products

Structural Equation Modeling (SEM) using RStudio was implemented to test the research model and hypotheses (Figure 3.8). Ease of use has been shown to have an influence on perceived utility (0.45), only partially confirming the H1 hypothesis. Hypothesis H2 has shown that perceived ease of use has a low influence on the attitude of use towards a product equipped with artificial intelligence (0.20). In the opposite way, the hypotheses H3 and H5 were revealed, where respectively with values of 0.76 and 0. 79 it was possible to observe a strong correlation between the perceived utility and the attitude for use and between the attitude of use towards of the behavioural intention to use, fully confirming the aforementioned hypotheses. Hypothesis H4, on the other hand, proved to be wrong as no correlation was found between perceived utility and behavioural intention to use.

In summary, the results of this analysis showed that only some of the theorized results in Davis' (1989) TAM model were validated by this data set. Hypothesis H4 did not meet expectations, H1 shows little correlation and H2 a fair amount, while H3 and H5 largely satisfied the hypotheses. There is a possibility that the perceived utility variable should not be used in the model to predict the behavioural intention towards the use and purchase of a product equipped with Artificial Intelligence.

Therefore, bearing in mind that the H4 hypothesis has proved to be incorrect and assuming a risk of multicollinearity, the model was proposed again without the relationship between perceived utility and behavioural intention (Figure 3.9). In this case the behavioural intention underwent a change since the correlation was no longer defined by two variables but by only one. Therefore, a better correlation can be observed, already strong previously, which led to an improvement from 0.79 to 0.84 in the correlation between the attitude of use towards the behavioral intention to use, making the H5 hypothesis more solid.

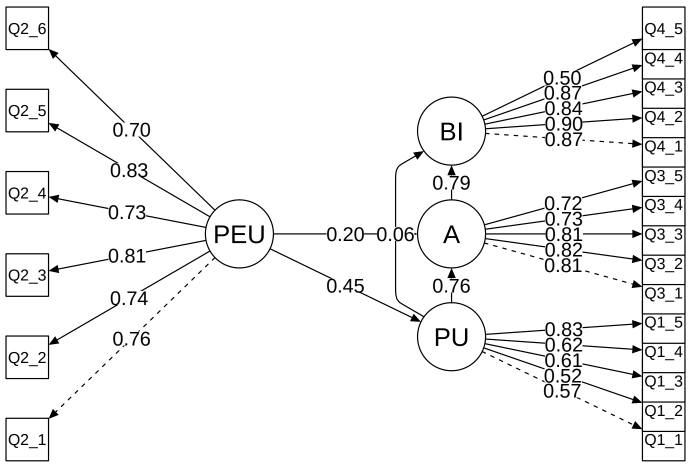

Figure 3.8: Path coefficients for products with AI.

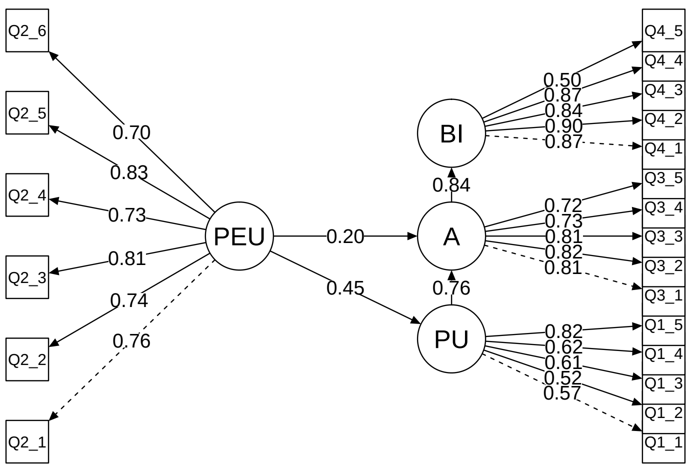

Figure 3.9: Path coefficients for products with AI w/o H4.

3.6.3 The Structural Model of the Most Chosen Products

Wanting to give a deeper evaluation to the survey, the model was also applied to the two most selected products by the interviewees who both represented 24% of preferences: self-driving cars and smartwatches.

Also in this case the Cronbach's alpha obtained most of the values close to 0.9 with only one case slightly lower than 0.7 but in line with values considered acceptable and the factor loading proved to be correctly loaded for most of the questions. In this case the TAM model was maintained without the H4 hypothesis, as in the second model seen above, to obviate the previously observed risk of multicollinearity. Difficulties were observed on the part of the software in running the SEM model with less data available and making the output variables incorrect if hypothesis H4 would be included.

Taking self-driving cars into consideration (Figure 3.10), it is possible to observe how the values reflect the trends observed previously where, however, the hypothesis H1 is more supported by the model with a value of 0.65 which allows to fully validate the correlation by validating it and where the hypotheses H3 and H5 they respectively obtain a correlation of 0.86 and 0.88, resulting slightly higher than what was seen for AI in a generic way, thus confirming the positivity of the hypotheses.

Instead, looking at the results obtained by smartwatches (Figure 3.11), values similar to those proposed in the model with the AI seen in a general way are observable. In this case the predicted hypotheses remain the same with a medium correlation of the H1 hypothesis, a low correlation of H2 and a strong correlation in the H3 and H5 hypotheses.

To summarize what has been seen with these two products, it is possible to consider that smartwatches do not differ from what has already been considered for the AI seen in a generic way, while self-driving vehicles have a further correlation compared to the other two models being able to count the positive relationship between perceived ease of use and perceived utility by adapting better to the 1989 Davis model.

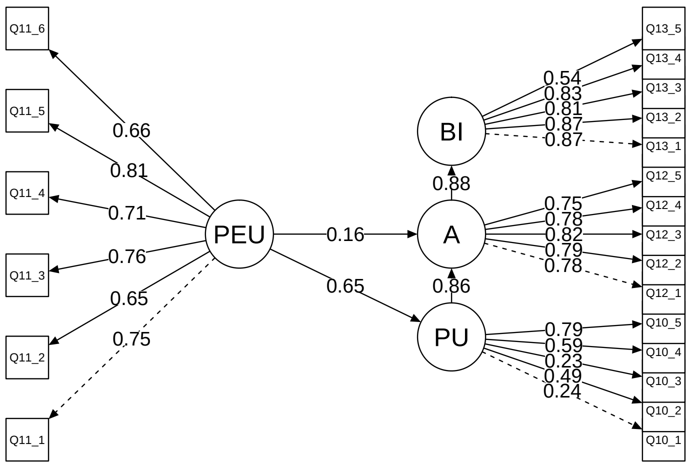

Figure 3.10: Path coefficients for self-driving cars.

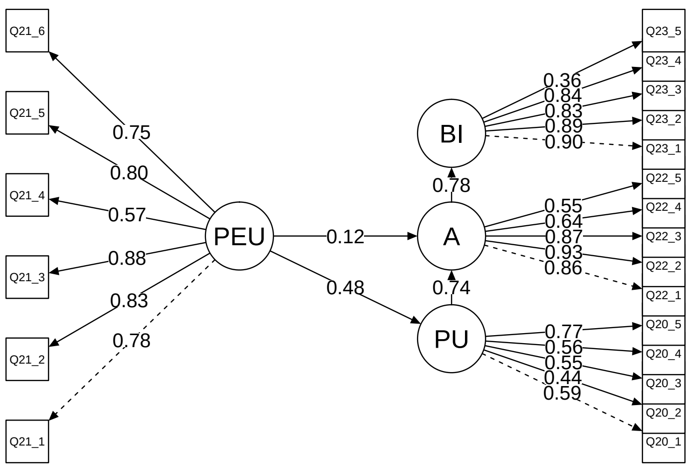

Figure 3.11: Path coefficients for smartwatch.

3.7 Discussion

The model proposed on AI validated most of the hypotheses with the exception of hypothesis H4 (The greater the perceived usefulness of a product with Artificial Intelligence, the more positive the consumer will behave towards the intention of adopting this innovation), which however was more taken into account, and the H2 hypothesis which had low correlation. In the models of the individual products chosen by the interviewees, the smartwatches turned out to be completely similar to what was stated, while self-driving cars would seem to have a stronger and stronger correlation than the H1 hypothesis that relates ease of use and utility perceived. The hypotheses H3 (The greater the perceived usefulness of a product with Artificial Intelligence, the more positive the attitude towards the adoption of this innovation) and H5 (The attitude towards the act of adopting a product with Artificial Intelligence has a direct and positive effect on the behavioural intention of the consumer to adopt this innovation) obtained positive results in all three SEM models, fully confirming what was hypothesized.

This leads to the consideration that a potential user of a product with Artificial Intelligence, perceived the usefulness of the same, is more inclined to its use and that the consumer's attitude towards the use of a product has a highly positive correlation in its subsequent use. It is also possible to observe how the perceived utility does not correlate with the behaviour of purchase and subsequent use, but a personal attitude is necessary to stimulate its subsequent purchase and/or use.

Furthermore, ease of use was not fundamental in the attitude of use towards a product with AI, overshadowing ease in favour of utility itself. Slightly different speech concerns self-driving cars, in this case in the other two models the correlation between perception of ease of use and perceived utility was moderate, while for autonomous driving the correlation was stronger. This result can be attributed to the complexity of the product which, compared to other choices, makes use of concepts of safety and trust superior to other products, thus leading the consumer to seek greater ease of use, making the product more suitable for future use.

According to Bentler and Chou (1987), in order to perform a good SEM analysis, the sample must have at least 200 observations. In this case, the observations available were 564 for the questionnaire on products equipped with AI and respectively 134 each for self-driving cars and smartwatches. The total number, taking into account that it represents the main research, turns out to be well above that requested by the two authors while for the two products it is slightly lower. However, the fact remains that, despite the number of observations having been largely exceeded, it is not sustainable to state that 564 observations are

sufficient to affirm and evaluate the technological acceptance of products equipped with AI and their future purchase and/or use.
Furthermore, the participants in the questionnaire proved to be mainly students (58%) and under the age of 30 (79%) therefore these models are more applicable to these samples. This result is also to be attributed to the methods of distribution, in a completely telematic manner, with advanced and innovative technology topics and distributed on social networks and mailing lists of the University of Aosta Valley. Finally, the type of product may not be completely known by all the interviewees, not allowing to imagine in a completely adequate way the possible interactions with it.
In the analysis of the results, no less important must be the evaluation of AI as GPT. Its complexity, supported by complex interrelationships with its components (Hogendorn & Frischmann, 2020), is to be linked to an expected delay on its implementation, to then obtain a significant impact on growth like the previous GPTs (Brynjolfsson, Rock & Syverson 2017; Cockburn, Henderson & Stem 2018; Aghion, Jones & Jones 2017; Agrawal, McHale & Oettl 2018; Trajtenberg 2018). Taking into account a theorized 10-year period from the actual delineation of the innovation to its full implementation and an attribution that took place only a few years ago, AI as a GPT is expected to need a period of between 5 and 10 years to be used by consumers who will discover the potential benefits offered. Furthermore, not being fully developed and with early proliferation, making it difficult to study future developments (Shimizu, 2019). The results obtained so far will therefore undergo probable upheavals in future years, reinforcing when it can already be found in the model.

Conclusion

This document has tried to illustrate crucial aspects of Artificial Intelligence both from the point of view of simple definition and by evaluating its applicability as General Purpose Technology. Not least was the applicability of a model of technology acceptance designed to outline the effects of perceived utility and perceived ease of use on people's attitudes and behavioural intentions towards the use of a commonly used product supported by Artificial Intelligence in the very near future or possibly at present. In fact, a series of products are already available that exploit AI to achieve the intended purpose but currently their functions are still rather limited and expectations are even more aimed at Machine Learning, a branch of AI that allows algorithms to automatically learn and process data to obtain increasingly precise results with respect to the user's choices.

A GPT, as stated by Lipsey, Carlaw and Bekar (2005) and contrary to the theory that technological change occurs at a constant pace within the economy, state that GPTs are defined as hardly predictable and bearers of revolutionary innovations at any moment, they are pervasive within the economy, improve over time and are generators of innovation. Similarly, Artificial Intelligence responds in the same way to these characteristics (Bresnahan & Trajtenberg, 1995) but, it is not yet fully developed, and the proliferation of their uses is only in its infancy, making it difficult to study future developments (Shimizu, 2019). Furthermore, technological innovations entail a significant change in consumer habits and therefore lead to implications regarding the changing behaviour towards the adoption of a new technology (Antioco & Kleijnen, 2010).

However, in order to evaluate the performance that products equipped with Artificial Intelligence can achieve, there is an interest in developing a research method that can effectively help predict the future and imminent acceptance of AI-equipped products by potential end users, providing a more practical and less abstract channel of applications on the most diverse products. From a literary point of view, applications concerning acceptance are more focused on individual applications of Artificial Intelligence or on theoretical definitions with no practical application. Therefore, there is a lack, or there is a reduced presence, of

analyses concerning generic applications on multiple products leaving little analysed the true nature of General Purpose Technology of AI based products.
In addition to offering an overview of the status of AI-enabled products, as these types of products will be developed in more different ways and evaluated by consumers more frequently as AI technology evolves, this paper also attempted to apply and empirically test a model research on the consumer's intention to use an AI based product by adapting it to a data set of 564 samples collected through an online survey. However, the development of this technology and its application to various fields are not enough to guarantee the use by consumers and the discovery of the potential benefits it offers. Therefore, an advanced knowledge of the success factors related to AI is required from the planning stage.
Everything was analysed by Davis' TAM model (1989) in order to obtain a complete picture of the perception by the end user. The model worked well, showing high correlations between almost all variables and a good fit with the dataset. This should represent a starting point for other studies in the sector that want to evaluate the degree of acceptance of products equipped with autonomous driving.
Furthermore, the type of analysis should be expanded to assess whether the results obtained are actually reliable and not limited to the restriction of the sample or of the analysis model. Further quantitative analyses should target both potential consumers, but also interested parties, in order to see if there is a match between their expectations about the future of consumer-facing applications of AI products. This type of future has already begun, but as stated by most of the literature, it needs time to be accepted and implemented. Artificial Intelligence and Machine Learning not only represent the latest discovery in terms of GPT but collect the importance of being the most important for our era (Brynjolfsson & McAfee, 2017). The discourse would no longer seem to concern the if and the how but more simply the when this technology will be able to be pervasive within society. The fact remains that AI together with ML allow innovation in many applications and are considered "invention of a method of invention", which suggests the importance of developing this type of technology and the potential and the greater economic impact than the development of each individual product (Cockburn, Henderson & Stem, 2018, citing Griliches, 1957).

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Appendix

Textual reworking of the questionnaire on Artificial Intelligence, presented within the report, distributed through the Qualtrics platform and dispensed only in Italian.

Inizio blocco: Anagrafica

Q1 Buongiorno, sono uno studente dell'Università della Valle d'Aosta e sto svolgendo un'analisi sul grado di accettazione dell'Intelligenza Artificiale (IA). Le chiedo di dedicare 5 minuti del suo tempo per rispondere ad alcune domande che mi aiuterebbero a completare il mio lavoro di tesi.
Le risposte e i dati raccolti saranno trattati in maniera totalmente anonima.
La ringrazio per la sua collaborazione.
André

Q2 Lei è:

- Maschio
- Femmina

Q3 La sua età è compresa nella classe:

- 18-30
- 31-40
- 41-50
- 51-60
- 61-70
- 70+

Q4 Il suo titolo di studio più alto è:

- o Licenza elementare/media
- o Qualifica professionale
- o Licenza media superiore
- o Laurea
- o Master/dottorato

Q5 La sua professione è:

- o Agricoltore
- o Artigiano
- o Operario
- o Impiegato
- o Dirigente
- o Imprenditore
- o Insegnante
- o Libero professionista
- o Studente
- o Pensionato
- o Non occupato
- o Altro

<u>Fine blocco: Anagrafica</u>

Inizio blocco: Spiegazione

Q6 L'Intelligenza Artificiale (IA) studia in che modo si possano riprodurre i processi mentali più complessi mediante l'uso di un computer. Alcune delle sue applicazioni attuali riguardano veicoli a guida autonoma, assistenti virtuali, smartwatch e fitness tracker, domotica, realtà aumentata (AR), chatbot, etc.
Ne ha mai sentito parlare?

- Sì, conosco l'argomento
- No, non ne ho mai sentito parlare
- Più o meno, so di cosa si tratta ma non ne ho una conoscenza specifica

Salta a: Fine blocco Se L'Intelligenza Artificiale (IA) studia in che modo si possano riprodurre i processi mentali più c... = Sì, conosco l'argomento

Q7 Ecco una breve descrizione di applicazioni dell'Intelligenza Artificiale:

- Gli assistenti virtuali sono software che interpretano il linguaggio naturale e possono dialogare con degli interlocutori umani allo scopo di fornire informazioni o compiere determinate operazioni (Siri, Google Now, Alexa, Cortana, etc.)
- Un chatbot è un software che consente agli utenti di interagire con i dispositivi digitali come se stessero comunicando con una persona reale (FAQ, customer care, supporto nell'acquisto su e-Commerce, diffusione di notizie, offerte e promozioni, etc.)
- I veicoli a guida autonoma sono sistemi che soddisfano le principali caratteristiche di trasporto tradizionale che, rilevando l'ambiente, attuano azioni senza alcun intervento umano (cruise control adattivo, mantenimento della corsia, rilevamento dei pedoni, frenata automatica, parcheggio automatico, etc.)
- La domotica rappresenta l'integrazione di dispositivi informatici integrati che permettano di automatizzare e facilitare l'adempimento delle varie operazioni solitamente svolte in un edificio (gestione automatizzata di elettrodomestici, termoregolarizzatori, illuminazione, irrigazione, etc.)
- Gli smartwatch e fitness trackers, sono orologi e braccialetti che monitorano i parametri vitali e possono essere usati per analizzare le informazioni vitali dell'utente fornendo valutazioni sullo stato di forma. Alcuni smartwatch

permettono di analizzare l'ECG, la pressione arteriosa, la temperatura, le aritmie, etc. I principali marchi sul mercato sono Garmin, Suunto, Polar, Fitbit, Apple Watch, Amazfit, etc.

- Per realtà aumentata (AR) si intende una realtà intermediata da uno strato virtuale (uno smartphone o un visore) che contribuisce ad arricchire quello che vediamo nel mondo reale con ologrammi che possono essere testi, immagini o modelli 3D. La realtà aumentata trova applicazioni in videogiochi, applicazioni scientifiche, applicazioni 3D, etc. (Pokémon Go, Peakfinder, IKEA place, etc.)

Fine blocco: Spiegazione

Inizio blocco: Scelta argomenti

Q8 Scelga e trascini nella casella laterale due dei prodotti con intelligenza artificiale che conosce o reputa maggiormente interessanti

o Veicoli a guida autonoma o Assistenti virtuali o Smartwatch e fitness tracker o Domotica o Realtà aumentata (AR) o Chatbot	

Fine blocco: Scelta argomenti

Inizio blocco: TAM *<prodotto selezionato>*

Questo blocco viene ripetuto due volte secondo le scelte selezionate in Q8. Le domande proposte sono le medesime per ciascun blocco e sono unicamente personalizzate per adattarsi al prodotto selezionato.

All'inizio di ogni blocco TAM viene proposta una breve definizione del prodotto selezionato per aiutare l'intervistato nelle risposte.

Q1TAM In base alla **percezione dell'utilità d'uso** di un *<prodotto selezionato>*, quanto si trova in accordo con le seguenti affermazioni?

	Completamente in accordo	Abbastanza in accordo	Né in accordo né in disaccordo	Abbastanza in disaccordo	Completamente in disaccordo
Un *<prodotto*	O	O	O	O	O

selezionato> mi aiuterebbe a risparmiare tempo					
Un *<prodotto selezionato>* aiuterebbe a fare meno sforzi	O	O	O	O	O
Un *<prodotto selezionato>* mi aiuterebbe a essere più produttivo	O	O	O	O	O
Un *<prodotto selezionato>* mi farebbe sentire più sicuro	O	O	O	O	O
Ritengo che un *<prodotto selezionato>* si rivelerebbe molto utile per me	O	O	O	O	O

Q2TAM In base alla **percezione della facilità d'uso** di un *<prodotto selezionato>*, quanto si trova in accordo con le seguenti affermazioni?

	Completamente in accordo	Abbastanza in accordo	Né in accordo né in disaccordo	Abbastanza in disaccordo	Completamente in disaccordo
L'uso di un *<prodotto selezionato>* risulterebbe facile	O	O	O	O	O
Dispongo delle conoscenze necessarie per utilizzare un *<prodotto selezionato>*	O	O	O	O	O
L'interazione con un *<prodotto selezionato>* risulterebbe chiara e comprensibile	O	O	O	O	O
Ritengo facile far sì che un *<prodotto selezionato>* faccia quello che voglio	O	O	O	O	O
Ritengo chiare e facili le istruzioni per adoperare un	O	O	O	O	O

<prodotto selezionato>					
Mi sentirei a mio agio nell'utilizzo di un *<prodotto selezionato>*, anche con le sue funzionalità più avanzate	O	O	O	O	O

Q3TAM In base alla **propensione all'uso** di un *<prodotto selezionato>*, quanto si trova in accordo con le seguenti affermazioni?

	Completamente in accordo	Abbastanza in accordo	Né in accordo né in disaccordo	Abbastanza in disaccordo	Completamente in disaccordo
L'uso di un *<prodotto selezionato>* nella vita di tutti i giorni risulterebbe piacevole	O	O	O	O	O
L'uso di un *<prodotto selezionato>* nella vita di tutti i giorni risulterebbe efficace	O	O	O	O	O

L'uso di un *<prodotto selezionato>* nella vita di tutti i giorni risulterebbe utile	O	O	O	O	O
Avrei fiducia di un *<prodotto selezionato>* per raggiungere lo scopo preposto	O	O	O	O	O
Preferirei usare un *<prodotto selezionato>* (se disponibile) invece di un prodotto convenzionale	O	O	O	O	O

Q4TAM In base al **comportamento d'uso** di un *<prodotto selezionato>*, quanto si trova in accordo con le seguenti affermazioni?

	Completamente in accordo	Abbastanza in accordo	Né in accordo né in disaccordo	Abbastanza in disaccordo	Completamente in disaccordo
Ho intenzione di usare un *<prodotto*	O	O	O	O	O

selezionato> nel futuro					
Ho intenzione di usare un *<prodotto selezionato>* frequentemente	O	O	O	O	O
Ho intenzione di raccomandare ad altre persone un *<prodotto selezionato>*	O	O	O	O	O
Ho intenzione di acquistare un *<prodotto selezionato>* nel futuro	O	O	O	O	O
Ho intenzione di usare un *<prodotto selezionato>* in un sistema di condivisione con altre persone	O	O	O	O	O

Fine blocco: TAM *<prodotto selezionato>*

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