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Faculty of Economics and Business

Bachelor's Thesis

Use of Technology and Big Data in E-Health Services

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Abstract

The objective of this work has been to analyze the factors that determine the acceptance and use of technology (TAM) in the field of health services as well as the design of an app focused on the prevention of cardiovascular diseases. The factors that determine the use of electronic devices in the health field are the utility or perceived value, the ease of use (simple and attractive interface), the interactivity of the user with the device, the attitude towards technology and the reduction of the perceived risk (protection of privacy and health risk).

From these determining factors, an app named Heart Focus App has been developed. This app would also make it possible to collect massive data from users or from databases from different official sources (FAO, INE, Ministry of Health) with the aim of predicting risk factors and providing information on healthier lifestyle habits. A data analysis based on statistical analysis techniques such as correlation analysis has identified a strong association between the elderly population and deaths from cardiovascular disease. Therefore, in view of the inevitable aging of the population, the development and use of electronic devices or apps with simple and easy-to-use interfaces, and the exploitation of big data derived from these can allow not only to improve the quality of life of patients, but also to reduce health costs and improve the quality of online and offline service.

***Key Words*:** Consumer Behavior, Technology, e-Health, Prevention, Big Data
Word Count: *14927*

Resumen

El objetivo de este trabajo ha sido analizar los factores que determinan la aceptación y uso de la tecnología (TAM) en el ámbito de los servicios sanitarios así como el diseño de una app focalizada en la prevención de enfermedades cardiovasculares. Los factores que determinan el uso de dispositivos electrónicos en el ámbito sanitario son la utilidad o valor percibido, la facilidad de uso (interfaz sencilla y atractiva), la interactividad del usuario con el dispositivo, la actitud hacia la tecnología y la reducción del riesgo percibido (protección de la privacidad y los riesgos para la salud).

A partir de estos factores determinantes, se ha desarrollado una app denominada Heart Focus App. Esta app también permitiría recoger datos masivos procedentes de los usuarios o de bancos de datos de diferentes fuentes oficiales (FAO, INE, Ministerio de Sanidad) con el objetivo de predecir factores de riesgo y proporcionar información sobre hábitos de vida más saludables. Un análisis de datos basado en técnicas de análisis estadístico como el análisis de correlación ha identificado una fuerte asociación entre la población de edad avanzada y las muertes por enfermedades cardiovasculares. Por ello, ante el inevitable envejecimiento de la población, el desarrollo y uso de dispositivos electrónicos o apps con interfaces sencillas y fáciles de usar, y la explotación de datos masivos derivados de estas puede permitir no solo mejorar la calidad de vida de los pacientes, sino también disminuir los costes sanitarios y mejorar la calidad del servicio online y offline.

***Palabras Clave*:** Comportamiento del Consumidor, Tecnología, Salud Digital, Prevención, Big Data

Número de Palabras: *14927*

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Introduction

Continuous innovation and the creation of new technologies have been the driving force behind society's development from the Stone Age, through the industrial revolution, to the present day. Specifically, the technological development of the 21st century has been clearly influenced by the emergence of computers, which have accelerated the process of innovation, favouring the use of new ways of generating and processing large amounts of data, new forms of communication such as augmented reality and new management tools such as artificial intelligence. Their applications are very numerous and varied, and they are currently being implemented in multiple sectors. However, there is one specific sector in which these new technologies have not yet made the qualitative leap that has occurred in other sectors (such as business through marketing intelligence, for instance), and that is the health sector, where the enormous potential offered by technology is still in the shadows. The entry of these new technologies into health centers and hospitals is expected to bring about a revolution in the health system, generating new health intelligence networks and improving the quality and efficiency of health services that will ultimately improve the quality of life, help to better manage health and reduce costs for the government in the long term.

The objectives of this bachelor's thesis are two: to review the literature on the acceptance and use of technology in health services, and to develop the Heart Focus application, which would serve not only to improve the cardiovascular health of patients but also to provide information and massive data (big data) to health centers, speciality centers or other management units supporting health authorities. To meet these purposes, this work has been structured in three clearly differentiated parts.

In the first part, the theoretical foundations are explained; highlighting the relevance of technology in business development, and presenting the Technology Acceptance Model with its main extensions, the concept of big data followed by some data analysis techniques —specifically hypothesis test for differences between means, correlation analysis and Google Analytics tool for websites and mobile apps analysis—, and the concept of user protection.

In the second part, the current literature on the use of technological applications in the health field and/or their acceptance is presented. The technologies that will be analyzed are, on the one hand, wearable health devices (WHD), augmented reality (AR) and artificial intelligence (AI) and automation, and on the other hand, big data analysis techniques applied to healthcare.

In light of what we have discovered in the previous part, in the third part, the mobile application Heart Focus is developed, followed by a data analysis application, whose purpose is taking a global look at cardiovascular disease and identifying present and new trends in a selection of developed countries, to better understand the dynamics and magnitude of the problem. Heart Focus highlights the great potential of the combination of technology (particularly wearable technology) and data analysis, for real-time patient monitoring and personalized prevention, among other benefits. Finally, the main conclusions extracted from the analysis are presented.

1. Theoretical Foundations

The irruption of new information and communication technologies (ICT) is transforming the economy and generating new forms of social communication. Its applications are increasingly numerous (e.g., big data analysis, internet of things (IoT), business intelligence, cibersecurity, etc.) and its reach is expanding, notably influencing the globalization of economic activities. It has also impacted the social life of consumers through the proliferation of social media platforms and even new forms of communication, hitherto unthinkable, such as holograms.

Hence, this market represents an excellent opportunity for businesses, despite being established by an environment of high competitive pressure, short lifecycles and a high change rate. Furthermore, the impact of new technologies on society should also be highlighted, since, for example, big data analysis is already being implemented in so-called smart cities to optimize the provision of services for citizens. However, research is increasingly necessary, not only to enhance the value or utility that technology can offer the customer or user, whether domestic or industrial, but also to protect them from privacy violations.

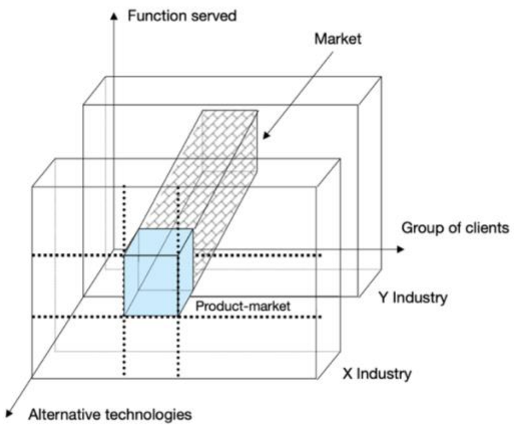
One of the models that has had the greatest impact in contributing to understand the phenomenon of the use of technology has been the Technology Acceptance Model (TAM), hence it will be investigated in this work, as well as some of its extensions. On the other side of the use of technology is the treatment of the generated data, and that is the reason why big data technology, data analysis techniques and user protection will be covered in further sections.

Therefore, the importance of technology is explained first, followed by the factors that influence the acceptance, use and dissemination of technology, the concept of big data, data analysis techniques and user protection.

1.1 Strategic Business Definition and the Importance of Technology

A strategic business unit, also known as product-market, can be defined following the three-dimensional model of professor Abell (1980). This author explains that business units are the result of the intersection of three dimensions: the group of clients –X axis–; the function served by the product or service –Y axis–; and the technology required for the product or service to perform their function –Z axis–. Therefore, a business unit, or product-market, would be defined as a set of consumers to whom a concrete need is satisfied by using a specific technology (see Figure 1). Namely, the market in question can be configurated as an independent and autonomous strategic business unit.

Figure 1: Strategic Definition of Business, Market and Industry

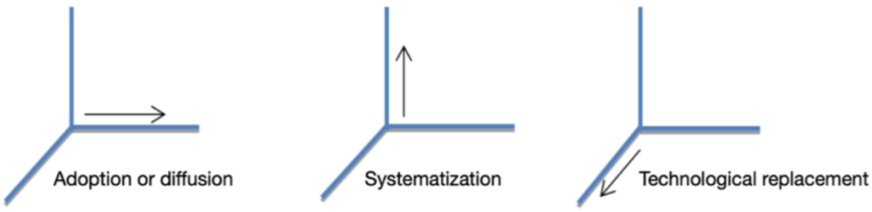


Source: Abell (1980)

1.1.1 Product-Market Extensions

This product-market or business may undergo modifications and evolve in each of the dimensions explained above, group of customers, alternative technologies and generic need function (see Figure 2). Logically, the most important will be technology.

Figure 2: Possible Product-Market Extensions



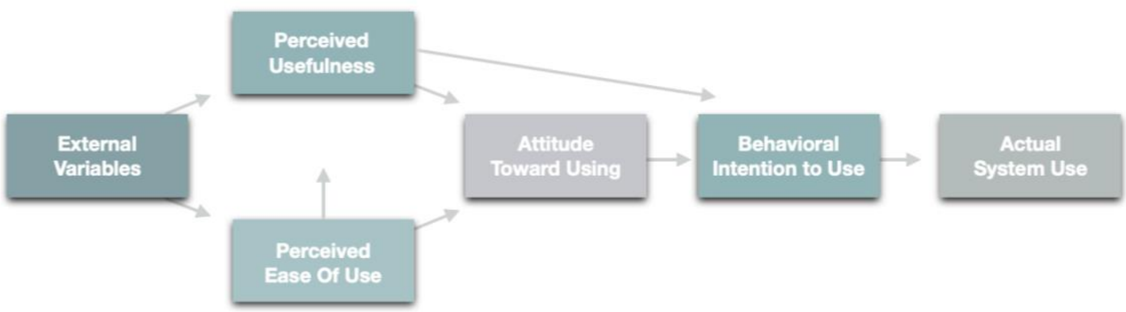
Source: Own elaboration from Abell (1980)

Adoption consists in the extension of the product-market or business towards new groups of customers, buyers or users. The systematization will consist of the extension of the market by redefining the space of generic needs (e.g., computers have been incorporating different functions such as calculator, word processor, etc). Lastly, the technology that consists in the extension of the market due to the appearance of new technologies or substitutes that cover the same generic need (e.g., smartphones replace the classic mobile phone).

1.2 Determining Factors in the Acceptance, Use and Dissemination of Technology

As Davis (1989) put it, the purpose of the Technology Acceptance Model (TAM) is to explain the causes behind the users' acceptance of technology, proposing that the perceived usefulness (PU) and ease-of-use (PEOU) of an information system are conclusive to determing their intention to use that specific technology (see Figure 3). According to this model, there exist different external variables that affect perceived usefulness and perceived ease-of-use directly, and the attitude towards using and final use indirectly.

Figure 3: Technology Acceptance Model



Source: Own elaboration from Davis (1989)

First, the most relevant concepts are explained, paying more attention to the great background such as perceived usefulness and ease-of-use. Then, the main extensions of this model are synthesized.

Perceived Usefulness

According to Davis (1989), the perceived usefulness of the use of technology is defined as the degree to which a person believes the use of a particular technological system will incease their performance or efficiency in the development of an activity. Logically, the greater the perceived usefulness, the greater the intention to use that technological product or service. This concept is crucial and decisive to understand the acceptance, use and diffusion of technology, so it is necessary to explain its components. Specifically, following Kotler & Keller (2012), the components of utility and perceived value are explained. The perceived value is a balance or result of comparing benefits and costs.

The benefits correspond to the positive aspects perceived in the product, service (added and basic) and its image. Among these product benefits are the functional or value aspects of use (e.g., internet connectivity, connection to platforms, etc.); technical attributes (e.g., weight, level of autonomy, size, etc.) and aesthetics (e.g., screen design, attractive icons, colors, etc.). Additionally, services that include customer service, consumer training, technical advice and product warranties should be taken into account. Subsequently, the image is highlighted, which can be defined as positive associations in the mind of the consumer.

On the one hand, the brand stands out from all the benefits. On the other hand, the price is logically emphasized among other costs (e.g., time, cognitive effort, physical effort, etc.), as it represents the economic sacrifice that the customer must endure to get the product or service in question.

Perceived Ease of Use

This dimension has been defined by Davis (1989) as the degree to which a person believes that the use of a particular system will be effortless.

In this sense, the TAM model predicts that the greater the perceptions of usefulness and ease of use, the greater the intention to use the system. Likewise, if the rest of the factors remain constant, the perceived ease of use will influence the perceived usefulness, since the simpler the use of the system, the more useful it will be. This concept reflects subjective evaluations of the system, and although they may not be representative of reality, the acceptance of a system would be resented if the user does not perceive it as useful and simple.

Attitude Toward Using

The attitudes measure the degree to which the result of an specific behavior is assessed positively or negatively (Ajzen, 1991). According to the TAM, the attitude should be positively related to the intention to use a given technological service.

Intention to Use

This dimension includes the cognitive representation of a person’s predisposition to perform a specific behavior. In this sense, it would be the direct antecedent of the actual use of a particular technological system.

External Influences: Trust and Risk

These are the factors related to perceived risk and trust. The risks include, above all, the psychological risk, which is the risk perceived by the user not knowing how to handle, use or understand the potential or benefits of the technology. Moreover, this psychological risk also takes into account privacy issues.

Logically, the greater the risk, the lower the attitude and intention of use, and the greater the trust, the greater the attitude and intention of use.

1.2.1 Extensions of the Technology Acceptance Model

The Technology Acceptance Model has been subject to many extensions throughout the years. Some of them are shown as following:

- Venkatesh & Davis (2000) developed a second Technology Acceptance Theory (TAM 2), which focuses on explaining perceived usefulness and usage intentions by means of social influence and cognitive instrumental processes.
- TAM 3, developed by Venkatesh & Bala (2008), adds new factors explaining ease of use, includes the moderating effects of experience and provides a comprehensive list of interventions that could enhance the adoption and use of information technologies in the workplace.
- A Unified Theory of Acceptance and Use of Technology (UTAUT) was also developed by Venkatesh et al. (2003) aiming to integrate eight previously established models.

In 2012, a second UTAUT was developed by Venkatesh et al. (2012). This paper focuses on the use and acceptance of technology at customer level, therefore new factors influencing behavioral intention and usage behavior –such as hedonic motivation, price value and habit–, and the moderating effects of age, gender and experience, are incorporated into this model. Applied studies based on the previously mentioned models will be explained in further sections.

1.3 Big Data

Big data has arised in the first decade of the 21st century through online and startup firms, as stated by Davenport & Dyché (2013). Large amouts of data used to constitute a problem, but it now represents a great opportunity for businesses (Russom, 2011). Analytics has become increasingly relevant for organizations worldwide since it has proven to provide valuable information for decision making (Gómez-Ullate Oteiza & Ríos Insua, 2019; McAfee & Brynjolfsson, 2012). According to Russom (2011, p. 5), "big data analytics is where advanced analytic techniques operate on big data sets". But, when does data start being considered as big data?. As Gobble (2013) put it, data becomes big data when it can not be handled by conventional systems.

The concept of big data rests on three fundamental attributes which were defined as the three V's of big data: volume, variety and velocity (Gómez-Ullate Oteiza & Ríos Insua, 2019; Kwon & Sim, 2013; Laney, 2001; Russom, 2011).

Volume refers to the large amount of data that is generated (Fosso Wamba et al., 2015; Gómez-Ullate Oteiza & Ríos Insua, 2019; Kwon & Sim, 2013). Due to its exponential growth, the magnitude of data has become a challenge for storage devices (Nguyen, 2019).

Velocity relates to the speed with which data is generated and evaluated for making real time decisions (Fosso Wamba et al., 2015; Gómez-Ullate Oteiza & Ríos Insua, 2019; Kwon & Sim, 2013; Russom, 2011).

Variety refers to the heterogeneity of the data generated since it comes from different sources and formats, and includes structured, semi-structured and unstructured data (Fosso Wamba et al., 2015; Gandomi & Haider, 2015; Gómez-Ullate Oteiza & Ríos Insua, 2019; Kwon & Sim, 2013; Russom, 2011).

Furthermore, the definition of big data has been extended to other dimensions, including:

Veracity has been defined as the fourth V by IBM (2012). It represents the uncertainty of some sources of data (e.g., social media networks) and highlights the relevance of cleaning the existing data (Gandomi & Haider, 2015; Jewell et al., 2014; White, 2012).

Variability. According to Gandomi & Haider (2015, p. 139), "variability refers to the variation in the data flow rates", which can be explained by the inconcistency of data velocity (Gandomi & Haider, 2015). On the other hand, Moretto et al. (2017) defines variability as the different interpretations that can be made from the same data. The idea of complexity was also attributed to big data by SAS, since it comes from very different sources and it makes the connection and treatment of data necessary (Gandomi & Haider, 2015).

Value refers to the identification of valuable data and its extraction for analysis (Nguyen, 2019; Oracle, 2013)**.** According to Gandomi & Haider (2015, p. 139), the analysis of large amounts of data allows to extract great value from big data, which "has a low value relative to its volume", and generate significant competitive advantages (Tan et al., 2015).

Figure 4: Characteristics of Big Data

Source: Own elaboration from Gandomi & Haider (2015)

Big data can be used for improving decision-making and productivity (McAfee & Brynjolfsson, 2012; Raguseo, 2018), reducing operating costs (Raguseo, 2018), supporting the procurement process (Moretto et al., 2017), the detailed exploration of customer behavior (Chau & Xu, 2012; Leeflang et al., 2014) and the discovery of new customer segments (Russom, 2011) among many other applications. A study carried out on 200 medium and large-sized French companies by Raguseo (2018) clasified the main benefits of big data into four different categories, namely strategic (provision of better products and services), transactional (increase of productivity), transformational (expansion of companies’ capabilities) and informational (improvement of data management, accuracy and access).

The competitive advantage of businesses is now fused with innovation through their big data competences (Jelinek & Bergey, 2013). Business survival will now be determined by customer’s perception of a product as new, even if it comes from a minor modification, and big data can generate multiple kinds of innovations (Jelinek & Bergey, 2013). A closer relationship between marketing and data analytics has led to digital marketing strategies (e.g., the use of social networks for the development of customer relations and brand building, the optimization of the customer journey...) supported by analytic tools (Leeflang et al., 2014). This suggests that marketers should adapt to the digital era in order to achieve higher performance (Leeflang et al., 2014; Perrey et al., 2013). Additionally, big data allows organizations to quickly adapt to changes in the environment, which is crucial for their over time sustainaiblity (Gómez-Ullate Oteiza & Ríos Insua, 2019; Jelinek & Bergey, 2013; Raguseo, 2018; Russom, 2011).

1.4 Data Analysis Techniques

1.4.1 Tools for Dealing with Time Series

A time series is defined by Montgomery et al. (2015, p. 2) as a “time-oriented or chronological sequence of observations on a variable of interest”. In chapter 4 of this work, several time series will be studied using two different techniques: test for differences between population means and correlation analysis.

Test for Differences between Population Means

To carry out a hypothesis test it is necessary to define a null hypothesis (H_0), that is the one being tested, and an alternative hypothesis (H_1), the one to hold when the evidence does not support the null hypothesis. Table 1 shows the characteristics of three possible hypothesis variations:

Table 1: Hypothesis Test Variations

Test Variation	Null Hypothesis	Alternative Hypothesis	Number of Tails
1	$\mu_1 = \mu_2$	$\mu_1 \neq \mu_2$	2
2	$\mu_1 \leq \mu_2$	$\mu_1 > \mu_2$	1
3	$\mu_1 \geq \mu_2$	$\mu_1 < \mu_2$	1

Source: Own elaboration from Newbold et al. (2013)

For the performance of these tests, we need two independent random samples (*n_x* and *n_y*) that come from normally distributed populations with means μ_x and μ_y (Newbold et al., 2013). As in the time series that will be studied the sample size does not exceed 100, the Student's t distribution will be the one used, assuming that population variances are equal despite being unknown (Newbold et al., 2013). Using the $\bar{x}$ and $\bar{y}$ means from the samples under study, Table 2 shows the decision rules corresponding to each test variation (Newbold et al., 2013):

Table 2: Decision Rules for Hypothesis Test

Test Variation 1	Reject H_0 if $\frac{\bar{x}-\bar{y}}{\sqrt{\frac{s_p^2}{n_x}+\frac{s_p^2}{n_y}}} < -t_{n_x+n_y-2,\alpha/2}$ or $\frac{\bar{x}-\bar{y}}{\sqrt{\frac{s_p^2}{n_x}+\frac{s_p^2}{n_y}}} > t_{n_x+n_y-2,\alpha/2}$
Test Variation 2	Reject H_0 if $\frac{\bar{x}-\bar{y}}{\sqrt{\frac{s_p^2}{n_x}+\frac{s_p^2}{n_y}}} > t_{n_x+n_y-2,\alpha}$
Test Variation 3	Reject H_0 if $\frac{\bar{x}-\bar{y}}{\sqrt{\frac{s_p^2}{n_x}+\frac{s_p^2}{n_y}}} < -t_{n_x+n_y-2,\alpha}$

Source: Own elaboration from Newbold et al. (2013)[1]

[1] Note: s_p^2 denotes a weighted average of the sample variances s_x^2 and s_y^2 (also named pooled variance estimator), n_x and n_y are the sample sizes derived from populations X and Y, respectively, and α is the signification level.

Correlation Analysis

The purpose of this analysis is to study and quantify the linear relationship between two variables (Newbold et al., 2013). One of the measures for the correlation analysis is the Pearson's correlation coefficient (r), which is calculated through the following formula:

$$r = \frac{\mathrm{Cov}(x,y)}{\sqrt{s_x^2 * s_y^2}} \qquad (1)$$

The covariance [(Cov(x,y)] and the variances for X and Y (s_x^2 and s_y^2, respectively) are calculated as follows[2]:

$$\mathrm{Cov}(x,y) = \frac{\sum(X-\bar{X})(Y-\bar{Y})}{n} \qquad (2)$$

$$s_x^2 = \frac{\sum(X-\bar{X})^2}{n} \qquad (3)$$

$$s_y^2 = \frac{\sum(Y-\bar{Y})^2}{n} \qquad (4)$$

The linear correlation coefficient is named r, and the values of r range between -1 and +1. On the one hand, the sign of the correlation coefficient denotes the direction of the relationship, which means that if it is negative, it represents an inverse linear association, and if it is positive, it represents a direct linear association between the two variables. On the other hand, the strength of the linear association between the variables is given by the magnitude of the coefficient, meaning that the linear association between the variables is strong if values are close to -1 and +1 (r values of -1 or +1 mean that there is a perfect linear fit regarding the variables, which involves the maximum strength or dependence between them), and if it is close to 0 it is weak (zero means that there is no linear association between X and Y) (Newbold et al., 2013).

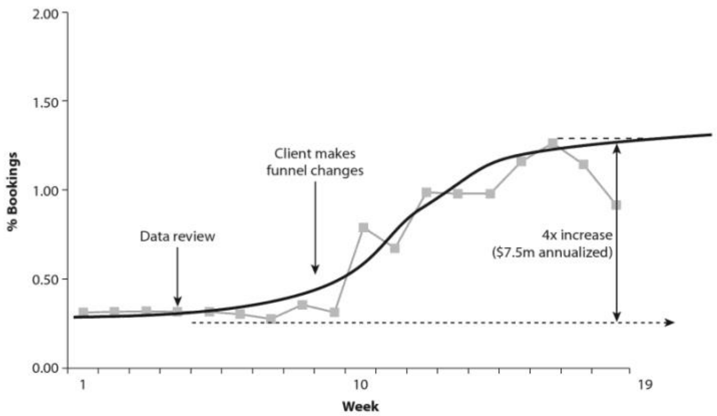
[2] In formulas 2, 3 and 4, $\bar{X}$ and $\bar{Y}$ are the sample means drawn from populations X and Y, and that n is the sample size.

1.4.2 Data Analytics

Due to the large size and complexity that data has developed in recent years, new technologies have emerged for the management and visualization of data (Dwivedi et al., 2016). According to Barlow (2013), cited by Dwivedi et al. (2016), data analytics is the science of exploring raw data with the purpose of obtaining useful information and discovering hidden patterns. In this sense, there are many data analytics tools that allow to extract meaningful information from data sets (Dwivedi et al., 2016).

Google Analytics is one of the main tools used in the field of website and mobile applications analytics. It is a free web analytics tool developed by Google that provides valuable information about a website's visitors and performance through the collection of data and the creation of reports (Clifton, 2012; Cutroni & Seiden, n.d.). This analysis includes information about the audience like demographics, interests and location; acquisition, which describes the way users arrive to a website; behavior, that analyzes how users interact with each page of a website; and conversion, which describes how website views become sales (Clifton, 2012; Cutroni & Seiden, n.d.). A research conducted by Hasan et al. (2009) have found that Google Analytics is a useful tool for evaluating a website's usability and for discovering potential problem areas. It can also be used for identifying growth opportunities, according to Clifton (2012).

Figure 5: Conversion Rate of a Travel Website Before and After Improvements



Source: Clifton (2012)

Figure 5 is an example of how the optimization of the funnel ("a well-defined process leading to a conversion goal") of a travel website can lead to a significant increase in the conversion rate of its bookings, which also translates into an increase in revenues (Clifton, 2012).

1.5 User Protection

Our society has been subject to a widely extended digitalization across industries and nations through the development of new technologies, which has allowed the collection and treatment of enormous amounts of data that are extremely useful for both government institutions and private companies. However, nowadays it is impossible to conceive the processing of personal data without its due protection, which is currently considered a human right, as stated in the *Charter of Fundamental Rights of the European Union* (2000).

Personal data has been defined in the EU Regulation *The protection of natural persons with regard to the processing of personal data and on the free movement of such data* (Regulation 2016/679) as “any information relating to an identified or identifiable natural person”, which specifically refers to those:

> ...who can be identified, directly or indirectly, in particular by reference to an identifier such as a name, an identification number, location data, an online identifier or to one or more factors specific to the physical, physiological, genetic, mental, economic, cultural or social identity of that natural person.

With recent cases of unauthorized use of personal data by companies such as Cambridge Analytica, the protection of the privacy of citizens has been the subject of debate. The repercussion of these practices goes beyond what one would have imagined, identifying personality traits of their users to influence their behavior through personalized messages, according to Isaak & Hanna (2018).

Nevertheless, the EU Regulation *The protection of natural persons with regard to the processing of personal data and on the free movement of such data* (Regulation 2016/679) states that some special categories of personal data –which includes health data– could be used for very specific purposes when strictly necessary (e.g., in the event of a cross-border health threat) if authorized by the competent agents and essential to protect vital interests, among other requirements.

2. Literature Review. Use of Technology and Information Processing in the Health Sector

Once the theoretical foundations explaining the factors that determine and condition the use of information and communication technologies (ICT) and some of the available techniques to analyze and treat this information (big data) have been exposed, specifically focusing on test for differences between population means, correlation analysis and an example of data analytics, we will present the main results and implications derived from the application of TAM and big data in healthcare.

The reason behind choosing this sector lies not only on its enormous potential to improve the well-being and health of patients or the performance of health professionals, but also because it would rise health services to the next level, for instance by providing health asistance without the need for travel, guiding surgeries with augmented reality and considerably reducing costs. In addition, digitalized health services would be a great source of information that would allow to identify the factors that predispose people to certain diseases, make early diagnoses or even manage a global health crisis.

This part has been divided into two sections. Firstly, the main applications of the Technology Acceptance Model (TAM), or its subsequent adaptations, to health services, are presented. We mainly focus on the intention to use electronic devices, monitoring and adherence to treatment applications, augmented reality and an application with great potential that is artificial intelligence. Secondly, we explain the process of big data analytics and benefits of its application in health care, both in a general way, and specifically in the case of chronic diseases. Among all the possible units big data could be applied to, the following stand out: hospitals, primary care units in health centers, crisis management or health emergency units, any unit with competences in the health area (e.g., Ministry of Health, Epidemiological Study Units, etc.).

2.1 Use of Technology and Health Services

2.1.1 Intention to Use Wearable Health Devices (WHD)

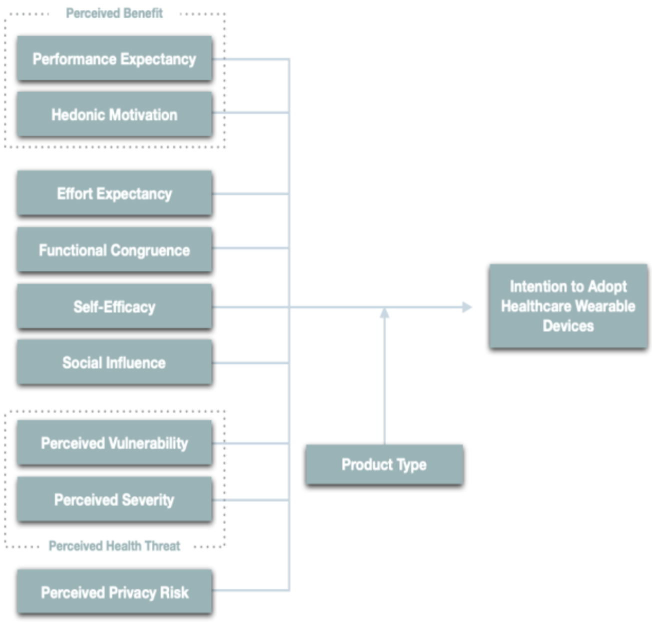
Gao et al. (2015) have investigated the adoption of WHD in healthcare, concluding that the intention to use it increases when perceived benefits exceed the loss of privacy. Also, product type has been found to have moderating effects. On the other hand, these authors stated that performance expectancy, effort expectancy, self-efficacy and perceived severity factors have the greatest influence on the use of WHD.

The first conclusion that can be drawn from our study is that there should not only be an expectation that the electronic device works, but also about the effort to develop, so very simple and easy-to-use devices should be sought, which reinforces the theory presented by Davis (1989) and Venkatesh & Davis (2000). Second, the user himself must perceive the effectiveness of the device –now called self-efficacy. From the intersection of these two factors, the challenge of developing handy and user-friendly electronic devices that are also portable would be highlighted. Third, the intention to use is also closely related to the perceived severity of the disease situation.

The conceptual model developed by Gao et al. (2015) is displayed in Figure 6. The UTAUT2 model developed by Venkatesh et al. (2012) was the one used as a basis to investigate the adoption of wearable health devices, eliminating factors such as habit because these devices are still entering the market, and including new ones such as those related to a perceived health threat.

Although the authors have not expressed which electronic devices would be more effective, manageability would be essential for their use. The most emphasized dimensions of the TAM model are perceived utility and ease of use. The latter stands out among the benefits for the user, and therefore the reduced effort and perceived utility, improving well-being. Finally, it is worth highlighting a more detailed investigation of the influence of perceived risk motivated by the privacy desired by the subject.

Figure 6: Conceptual Model of Wearable Technology Acceptance in Healthcare

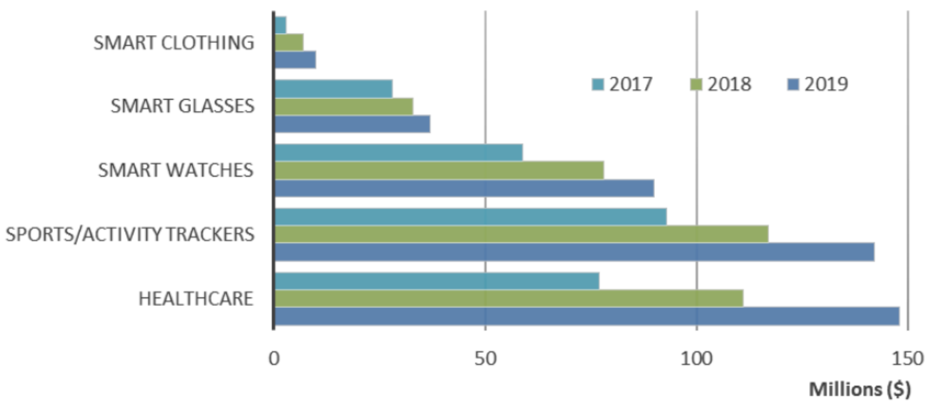


Source: Own elaboration from Gao et al. (2015)

2.1.2 Follow-up Applications and Treatment Adherence

The development of Wearable Health Devices (WHDs) has enabled monitoring human vital signs in the performance of day to day activities and in clinical environments (Di Rienzo et al., 2006). Global market trends show that the applications of wearable devices are going to focus on healthcare according to the following graph from Dias & Paulo Silva Cunha (2018).

Figure 7: Horizontal Bar Graph Showing the Trends of Global Market Value of Wearable Devices in Millions from 2017 to 2019

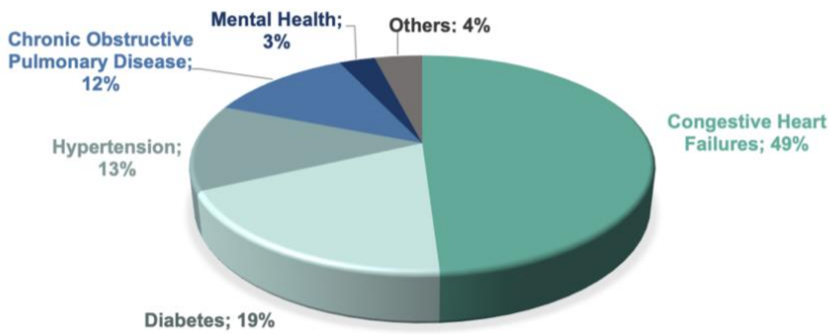


Source: Dias & Paulo Silva Cunha (2018)

Healthcare applications of this technology range from self-monitoring and rehabilitation processes –activity monitoring category–, to the anticipation of medical events, identification of anomalies and clinical decision making –medical category– (Banaee et al., 2013; Dias & Paulo Silva Cunha, 2018).

In order to study the acceptance of wearable devices in health monitoring and treatment adherence we are going to focus our attention on chronic diseases, which concentrated a vast majority of the telemedicine market in 2014, as Figure 8 shows.

Figure 8: World Market for Telehealth from 2014 Classified in the Main Areas



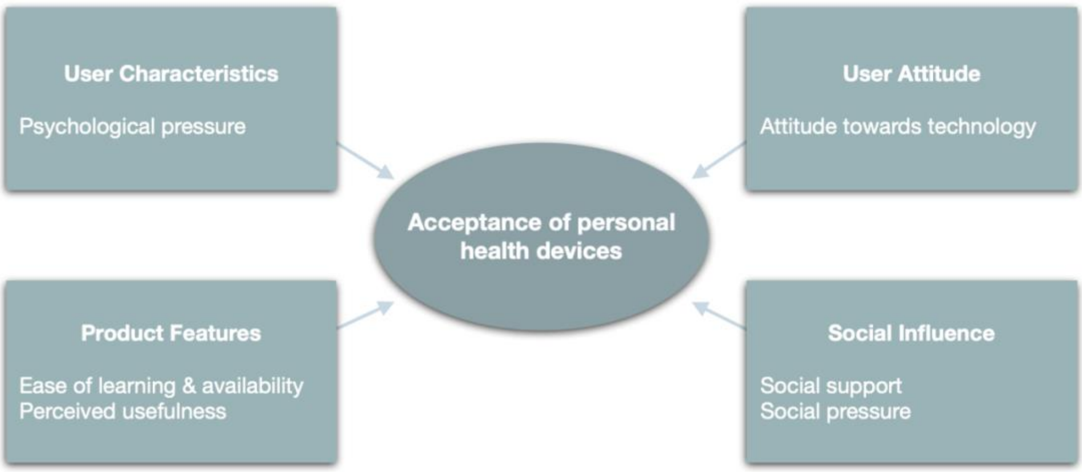
Source: Own elaboration from Dias & Paulo Silva Cunha (2018)

The acceptance of personal health devices among patients with chronic conditions has been studied by Sun & Rau (2015), who created an acceptance model to display the five factors affecting its adoption.

The most important factor on WHD's acceptance is **attitude towards technology**, specially among the elders, because they experiment greater adversity when using these devices (i.e., having brief experience, lower physical and cognitive capacity...); the second factor is **ease of learning and availability**, suggesting that devices should be simple and easy to use while also maintaining long battery life and accuracy; the third factor is **perceived usefulness,** which refers to the benefits of using WHD (e.g., staying healthy, increasing independance via reminders and emergency alerts); the fourth factor is **social support** from family, friends and medical professionals (i.e., sharing health data with medical professionals by connecting devices to an e-health system); and the fifth factor is **perceived pressure**, which refers to both social pressure (which fosters devices to be designed as an indicator health instead of sickness), and psychological pressure (that justifies electronic medical support and assistance to alleviate an anxious use of these devices by patients).

All the factors integrating this model can also be found in previously studied models such as UTAUT 2 developed by Venkatesh et al. (2012) which includes habit and experience, effort expectancy, performance expectancy and social influence, and extensions of that model like the one carried out by Gao et al. (2015) with factors like perceived vulnerability and perceived severity. Figure 9 provides a visual summary of the factors influencing the acceptance of WHD by patients with chronic conditions, divided into four categories:

Figure 9: Acceptance Model of Personal Health Devices by Patients with Chronic Conditions



Source: Own elaboration from Sun & Rau (2015)

The role of wireless technology in the treatment and monitoring of these diseases has been studied by Geisler & Wickramasinghe (2019) and the following conclusions have been extracted:

Firstly, the application of wireless devices and mobile phone technology in this medical field contributes to an improvement of the access to care, the quality of care, and a reduction of its costs, which is crucial in countries such as the United States where many patients with chronic diseases are uninsured or underserved due to economic constraints. And secondly, the large amounts of data collected by wearable devices allow further research on these diseases, in which early detection would avoid additional complications that, for example, in the case of patients with diabetes, would reduce morbidity and mortality.

2.1.3 The Role of Augmented Reality in Healthcare

Augmented reality (AR) technology has enabled to enrich reality by adding virtual/artificial elements to it in real-time and in three dimensions (Azuma, 1997). Many applications have been developed in very different areas and academic disciplines (Azuma, 1997; Carmigniani et al., 2011; Zhu et al., 2014) such as the military, education, medicine and advertising. In medicine, they range from the training of medical students, to the performance of delicate surgeries (Barsom et al., 2016; Son-Lik Tang et al., 1998).

Attitudes towards the use of AR in healthcare are generally positive. Studies developed by Gallos et al. (2019) and Rasimah et al. (2011) show that usefulness and ease of use (Davis, 1985) are the main factors affecting the adoption of AR both in healthcare and medical training. Nilsson & Johansson (2008) highlighted interactivity as the element that would considerably increase the adoption and usefulness of AR, as well as making it more similar to human interactions. Experience has also been mentioned as an important factor in the adoption of medical AR applications according to a study conducted by Nilsson & Johansson (2008).

Some of the applications of AR in the health sector are related to education, as it enables safe medical training (Barsom et al., 2016). The perceived ease of use of learning systems was found to increase the perceived enjoyment of students (Rasimah et al., 2011), nevertheless, enjoyment has a weak influence on its adoption (Venkatesh & Bala, 2008). The authenticity of the experience provided by AR enhances student's subjective attractiveness, and also leads to the development of abilities such as space vision, decision making, and learning retention (Barsom et al., 2016; Zhu et al., 2014). Overall, AR enhaces student's engagement (Moro et al., 2017), which contributes to an improvement of the learning process. Wake et al. (2019) have investigated the impact of 3D printed and AR models in patient education and concluded that although AR models were valuable for patients, they did not increase patient understanding in anatomy, disease or treatment choice.

AR technologies have also been used in the development of surgical applications. Some of the advantages of using this tecnology are precision in motion sensing, high definition display, data handling capacity and speech recognition. The last mentioned benefit is decisive in the operating room because it does not require any form of physical contact (Thomas, 2016). A real-time access to information could really expand the possibilities in this field (Lindeque et al., 2014; Vávra et al., 2017).

2.1.4 Artificial Intelligence and Automation

Artificial Intelligence (AI) refers to “the concept of creating computer programs or machines capable of behavior we would regard as intelligent if exhibited by humans” according to Kaplan (2016, p. 1). This technology has allowed the development of several applications in the health field, such as the detection of anomalies in radiology images with an intelligent assistant, the diagnosis of several conditions through deep learning algorythms or speeding the development of therapies in pharmaceutical companies using supercomputers (Meskó et al., 2018). Furthermore, the recent COVID-19 pandemic has highlighted the importance of AI in crisis management.

This issue has been reviewed by Vaishya et al. (2020), in whose article explains the main applications and benefits of AI in the management of health crises. On the one hand, Vaishya et al. (2020) explains that its applications include the detection of abnormalities and early diagnosis, treatment monitoring, follow-up of contacts between individuals, forecasting of new cases and mortality through available data and social media, accelerating the development of medicines/vaccines, reducing oversaturation of healthcare and preventing the disease through real-time data analysis. On the other hand, the benefits of this technology in health crisis management are easily tracing the spread of the virus, identifying patients with a higher risk and generating suggestions about how to control the infection. In addition, incorporating AI into treatment increases precision and reduces complexity and time spent. However, the use of personal data (e.g., location) is subject to debate as it is seen as a privacy violation. Thus, the enhancement of privacy (Gao et al., 2015) would be key to the adoption of AI. A possible solution to the problem could be to strictly use the data needed to control the spread of the virus in an anonymous way, without ever associating it to personal data.

At the other end of health crisis management are robots and WHDs. Nowadays, service robots exhibit a high degree of autonomy, are able to communicate with the environment and also understand human actions (Haidegger et al., 2013). In this sense, robots can contribute to the alleviation of the health system saturation by monitoring vital signs, giving medicines (Alvarez et al., 2018), facilitating communication (Koceski & Koceska, 2016), and keeping patients company (Zukowski et al., 2018). Additionally, the automation of information flows through wearable devices (i.e., generating notifications or alerts when blood pressure indicators hit certain levels) help reduce the economic and cognitive costs of information processing. All these services are crucial in the prevention of a pandemic of the magnitude of COVID-19.

Table 3: Table of Research Review

Author/s	TAM model applications	Purpose of the application	Dimension/s to enhance (in TAM model) and other results of interest	Benefits or result achieved by this investigation
Gao et al. (2015), Davis (1989), Venkatesh & Davis (2000)	**Connectivity to an Electronic Device**	Improve the well-being of the user thanks to the advantages conferred by connectivity through an electronic device	**Perceived utility** and **ease of use**	There must be an expectation that the electronic device works and also of the effort to develop. Second, the user himself must perceive the effectiveness of the device, which has been called self-efficacy. Third, the intention to use is also closely related to the perceived severity of the disease situation or context.
Dias & Paulo Silva Cunha (2018), Banaee et al. (2013), Sun & Rau (2015), Geiser & Wickramasingher (2019)	**Follow-Up Applications and Treatment Adherence**	Achieve greater involvement of the patient in the treatment of pathologies	**Attitude towards technology** (specially among the elders), **ease of use** and **perceived utility.**	These devices allow activity tracking for self-monitoring and rehabilitation processes. An improved communication between patients and medical professionals allows the personalization of healthcare services. In addition, wearable health devices improve the access to medical care of patients with chronic diseases, and the quality of care, and also reduces economic costs for the public sector. On the other hand, the data collected allows to anticipate and predict diseases, thus avoiding complications.
Gallos et al. (2019), Rasimah et al. (2011), Nilsson & Johansson (2008), Moro et al. (2017), Barsom et al. (2016), Zhu et al. (2014), Thomas (2016), Lindeque et al. (2014), Vávra et al. (2017)	**Augmented Reality Devices**	Improve communication between the patient (and family) and healthcare personnel.	**Trust** (for the patient) and **usage value** for healthcare personnel. **Interactivity** has also been highlighted as a relevant factor influencing the adoption of AR technologies in healthcare.	On the one hand, it creates a safe environment for training, improves the learning process and increases the engagement of students. On the other hand, AR increases the quality of surgical interventions mainly through higher precision and the access to information in real-time without the need of physical contact.
Vaishya et al. (2020), Haidegger et al. (2013), Gao et al. (2015), Koceski & Koceska (2016), Alvarez et al. (2018), Zukowski et al. (2018)	**Artificial Ingelligence and Automation**	Manage and prevent the spread of disease and improve access and quality of medical care.	A reduction of **privacy risk** is needed in order to incorporate these technologies to the management of crisis.	Improved management of health crises through forecasting and control of the spread of the disease, greater efficiency and identification of patients at risk. Robots contribute to the alleviation of the healthcare system through the reduction of the workload of caregivers and the increase of the independence of patients.

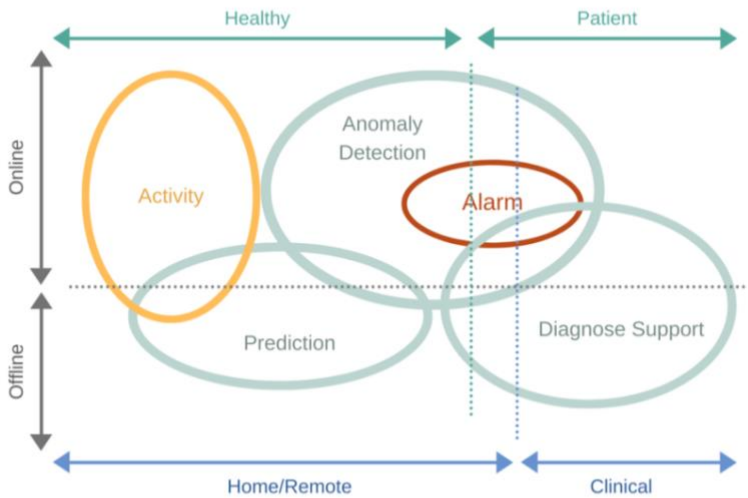
Source: Own elaboration

2.2 Smart Healthcare or E-Health Centers (Big Data)

2.2.1 Connectivity and Healthcare

The increasing use of wearable health devices (WHD) has been crucial in boosting remote health services, leading to a growing generation of data that expands the capabilities of health systems by enabling improved quality of health care through greater precision in analysis and prediction (Wang et al., 2018). The collection of health data over long time periods outside clinical environments has proven to be very useful since it allows the anticipation and prediction of diseases, the elaboration of more solid diagnosis, and better and faster recoveries from medical interventions or physical injuries –which are some of the main applications of WHD shown in Figure 10– according to Dias & Paulo Silva Cunha (2018). These authors also highlighted the importance of collecting information about the environment of each user, so that, for instance, in the case of the elders, it is possible to consider circumstances such as long exposure to excessive cold or hot temperatures which could lead to several health complications.

Figure 10: Overview of the Four Main Data Mining Processes in Relation to Different Aspects of Wearable Health Devices

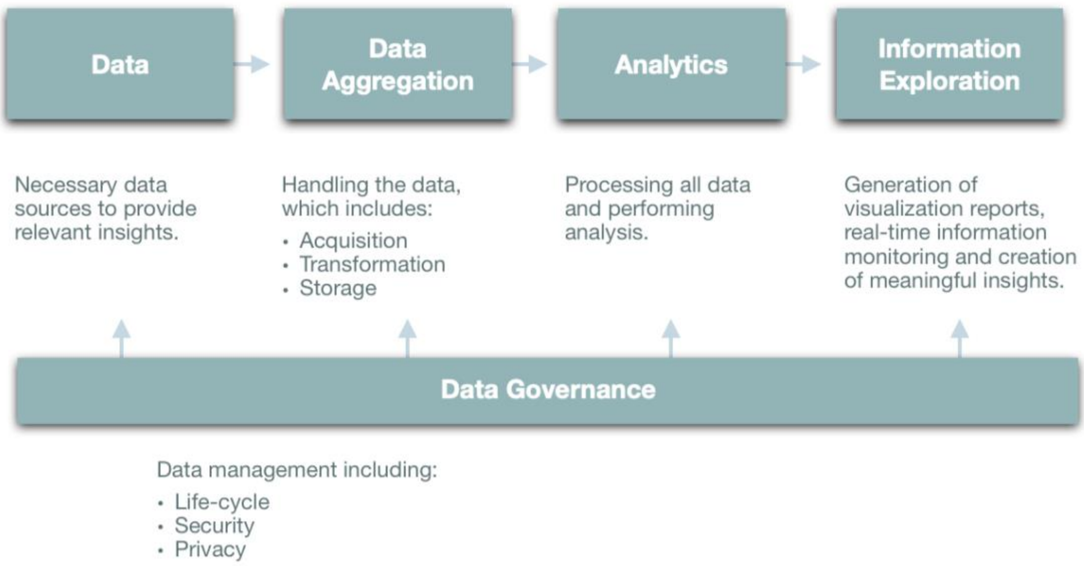


Source: Own elaboration from Dias & Paulo Silva Cunha (2018), adapted from Banaee et al. (2013)

A simple example of connectivity in healthcare would be a personalized health system developed by Hahanov & Miz (2015) that collects data through WHD and is capable of identifying patterns to detect possible anomalies, and of evaluating health data and sending recommendations to its users.

The processes and capabilities of data analytics in healthcare have been analyzed and structured by Wang et al. (2018) in order to foster its integration in health systems. First, the phases that compose the data analytics process are briefly explained in Figure 11:

Figure 11: Layers of Data Analytics



Source: Own elaboration from Wang et al. (2018)

Second, healthcare data analysis capabilities, according to the report by Wang et al. (2018), are summarized as follows:

- **Analytical capability for patterns of care.** This refers to the identification of unnoticed patterns and relationships based on the study of large health records.
- **Unstructured data analytical capability.** With 80% of health data being of this type, their analysis could significantly transform health care management.
- **Decision support capability.** The generation of reports showing real-time or summarized information allows to personalize care, detect alerts for disease monitoring and recognize improvement opportunities.
- **Predictive capability.** It reduces the level of uncertainty through better and faster decisions, the optimization of services and the identification of future healthcare trends based on patients' lifestyle, habits and monitoring.
- **Traceability.** It facilitates meeting the needs of patients by improving consistency, visibility and access to data.

The main trends of data analysis process, according to Wang et al. (2018), are cloud computing services –which are implemented at the data aggregation layer as they support real-time analytics and reduce the cost of storage– and a shift from structured data to semi-structured data, like home monitoring or WHD, and unstructured data, such as images or video. In addition, Zheng et al. (2013) have predicted that wearable technology will shift from hospital-centered health care systems to new systems that focus on the individual, their family and the community.

Finally, from the research carried out by Wang et al. (2018) we can extract that the application of data analysis to healthcare allows to optimize health services by increasing the efficiency and effectiveness of information flows.

2.2.2 Chronic Diseases

Chronic diseases are on the rise worldwide, which is considerably challenging the healthcare sector in some countries. The big presence of chronic diseases in the United States –which affect to half of the American population–, also involves big costs. The treatment of chronic diseases covers 80% of an American's medical health fee and an 18% of the annual GDP of the United States. Another example is China, which is also deeply affected by chronic diseases, since they are the main cause of death, representing a 86,6% of deaths in 2015 according to Chen et al. (2017).

As it has been mentioned on previous sections, wearable technologies allow the generation of large sets of data, which can provide very valuable and useful information for the management of chronic diseases and also a reduction of costs. This issue has been reviewed by Groves et al. (2013) and Lin et al. (2018), from whose studies we can extract that big data technologies drive better analytical capabilities that can be used to identify the factors that lead to specific medical conditions, measure the effectiveness of treatments or identify patterns related to side effects or readmissions related to certain medicines. According to Groves et al. (2013), resistance to change, uncertainty in the returns of information technology investment and privacy concerns are some of the elements that slow down the implementation of big data technologies in healthcare.

The most relevant applications of big data in chronic diseases are based on its predictive capabilities. This subject has been reviewed by Barrett et al. (2013), who identified two ways in which big data can improve disease prevention: through research and interventions.

First, Barrett et al. (2013) explained two major ways in which big data enriches the investigation of new risk factors. On the one hand, big data allows to improve regular epidemiologic studies through the personalization of analysis. By taking the analysis from a population level to certain segments or even to a personal level, more variables can be included, and therefore, more valuable information can be extracted. In addition, the discovery of new relationships between certain risk factors and concrete individuals allows more personalized information to be sent to patients, thus improving prevention. On the other hand, new passive sensors –such as those that have been integrated into the wearable devices mentioned in the previous sections–, allow the collection of data in real time and for long periods, which also enriches the analysis of risk factors through access to more complete and accurate data.

Second, they explain how big data can be used in interventions to prevent diseases. According to Barrett et al. (2013), the use of big data considerably extends the reach of prevention efforts, as it allows to turn punctual doctor recommendations that usually take place once or twice a year, into personalized advice messages that reach every patient without the need to visit the healthcenter personally. These authors also mention an interesting cycle that would be generated through the use of individualized and detailed data from patients to conduct research, which then would reflect back on patients through more effective interventions, thus generating more data that could be included in further research studies.

The main concerns surrounding the use of big data in healthcare have to do with privacy, specially with the maintainance and access to huge databases that combine all the health information about patients that has been gathered through time, according to Barrett et al. (2013). Despite the introduction of big data analysis entails a serious challenge for health organizations, the benefits of its use both to patients, through an improved health, and to healthcare, by the reduction of costs, make it worth the effort.

3 Empirical Evidence

3.1 Problem Statement

According to the World Health Organization (2018), cardiovascular disease has been the leading cause of death worldwide in the last 15 years. Some of the risk factors associated with the development of heart disease cannot be changed, for example, age, gender, family history, or race. However, there are a number of factors that can be modified by patients, reducing the risk of contracting cardiovascular disease. Among these modifiable factors are high blood pressure, cholesterol, diabetes, and also a lack of regular exercise, smoking or a poor diet.

Firstly, aiming to address the modifiable factors leading to cardiovascular disease and also, to show the innovation possibilities offered by the fusion of marketing and new technologies in preventive medicine, a mobile application has been devised from scratch. This issue has been approached by three different perspectives:

- Monitoring and prevention of cardiovascular disease at the **user** level with great comfort and precision through the use of wearable health devices.
- Treatment adherence control and improved diagnosis through new information flows between patients and **medical** professionals.
- The control and development of preventive policies at the **institutional** level through the collection and analysis of large data sets through big data analysis techniques.

Secondly, this App will be complemented by statistical studies on prevention at a national level –specifically using a test for differences between population means and correlation analysis– which aim to answer the following questions: Have the cardiovascular disease prevention programs implemented in several countries succeeded at reducing the deaths caused by this type of disease? Does the aging of the population explain the recent increase in deaths caused by cardiovascular disease worldwide?

3.2 Heart Focus: Cardiovascular Disease Prevention App

Heart Focus is a cardiovascular disease prevention App that collects health data from wearable devices in order to help users monitor their cardiovascular health through different indicators such as blood pressure or levels of physical activity. On the other hand, the data collected will be shown to authorized doctors for treatment follow up and gathered together anonymously in different databases for authorized institutions to analyze. The purpose of the Heart Focus App is to prevent heart disease worldwide and to become a leading source of data for cardiovascular disease management.

Competition Analysis: Heart Applications

A brief analysis of the competition is carried out to find out which are some of the cardiovascular applications currently present on the market and what elements characterize each of them in terms of purpose and risk factors monitored. The identification of these mobile apps has been made through several Google and App Store searches such as: heart disease prevention App, cardiovascular disease prevention App, heart disease or cardiovascular disease.

The most frequent purpose of these applications is self-monitoring, followed by educational or informative purposes. Four out of fourteen apps are dedicated to prevention or recovery puposes at a user level, other four contribute to medical control through shareable reports or medication scheduling, and only one aims to make contributions to research studies. There has only been found one application that uses augmented reality technologies, and it is specially aimed at educational purposes.

Table 4: Purpose of Mobile Heart Applications

APP NAME	Self-monitoring	Prevention or recovery (HD)	Medical Control	Contribution to research	Educational/ informative	AR Tech
Cardiogram	x	x		x		
FitBit	x				x	
Qardio	x		x			
My Cardiac Coach	x	x			x	
Smart Blood Pressure	x					
iCardio	x				x	

Cardiio	x					
Blood Pressure Companion	x	x	x			
Instant Heart Rate	x		x			
Pulse Into	x					
CardioVisual		x			x	
ASCVD Risk Estimator	x		x			
Cardio Smart					x	
cARdiac ECG					x	x
Heart Focus	x	x	x	x	x	x

Source: Own elaboration

Regarding the risk factors measured, most of the mobile applications that have been analyzed focus on the monitoring of heart rate, specially associated with physical activity and exercise. Less than half of them measure blood pressure or cholesterol levels, which are key indicators for the detection of cardiovascular diseases. Lifestyle indicators, such as diet, smoking and drinking, stress or sleep, are primarily related to general health or fitness control, rather than prevention purposes.

Table 5: Risk Factors Monitored by Mobile Heart Applications

APP NAME	Heart Rate	Blood Pressure	Cholesterol	Exercise	Diet	Smoking/ Alcohol	Weight	Sleep	Stress
Cardiogram	x			x	x	x		x	x
FitBit	x			x	x		x	x	x
Qardio	x	x		x	x		x		
My Cardiac Coach	x	x	x	x			x		
Smart Blood Pressure	x	x					x		
iCardio	x			x					
Cardiio	x			x					
Blood Pressure Companion	x	x					x		
Instant Heart Rate	x			x				x	x
Pulse Into	x			x					
CardioVisual									
ASCVD Risk Estimator		x	x			x			
Cardio Smart									
cARdiac ECG									
Heart Focus	x	x	x	x	x	x	x	x	x

Source: Own elaboration

As far as we know, there is no mobile application that brings together the monitoring of so many risk factors, informs and educates users, and contributes to research, medical control and the development of prevention policies through the collection of health data in real time.

3.3 Acceptance of Heart Focus

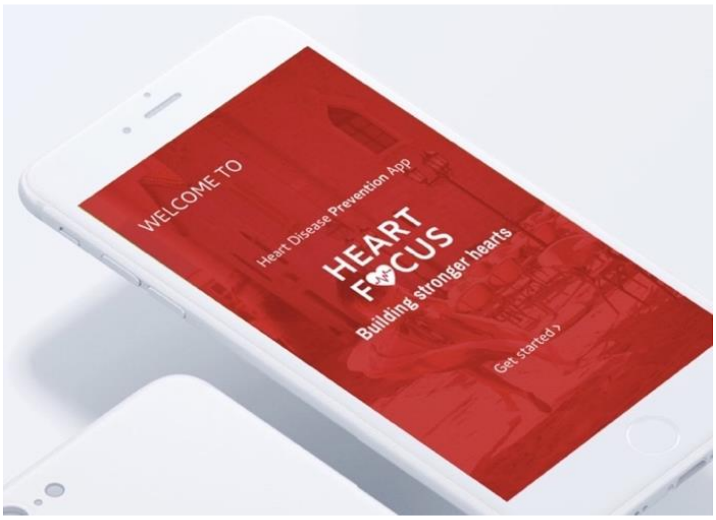
In this chapter, the acceptance of the Heart Focus mobile application will be analyzed. Four factors were chosen as the main elements influencing adoption: ease of use, utility, interactivity, and perceived health threat and psychological pressure.

3.3.1 Ease of Use

This issue will be approached from two different perspectives: mobile application design and devices used. The ease of use of Heart Focus is expressed through a solid identity and an adapted design, which is the result of the following strategic decisions. The whole App concept revolves around the heart, which explains the selection of the red as its corporate color, evoking feelings of action, love, energy and attention.

Font choices are also relevant because the majority of its users are adults that may suffer from vision problems, so the main consideration that should be taken is that all information must be easy to read. In this sense, large, clear fonts such as those shown in Figure 12, and short texts with prominent words or phrases, are preferred.

Figure 12: Identification and Access to Heart Focus



Source: Own elaboration

In order to improve the self-efficacy of the users and to facilitate their learning process, the content structure must be simple, and its design must be very intuitive. This is one of the reasons why Heart Focus App offers three access options: user/patient access, a medical access and an institutional access.

From the point of view of wearable devices, the best suited to the data needs of this App are smartwatches, which are widely used worldwide due to their ergonomic and comfortable design. They can be easily connected to mobile phones through Bluetooth technology and automatically collect multiple types of user health information while performing daily activities, exercising, or sleeping. Devices used for this purpose must require little physical and mental effort, since the majority of their users will be elderly. They should also maintain adequate battery life and measurement precision, because in addition to conditioning their ease of use and learning, they will determine their usefulness. Most available smartwatches can measure heart rate, steps, calories and sleep, but only the most advanced ones incorporate blood pressure measurement.

Figure 13: Example of Smartwatches that Measure Blood Pressure

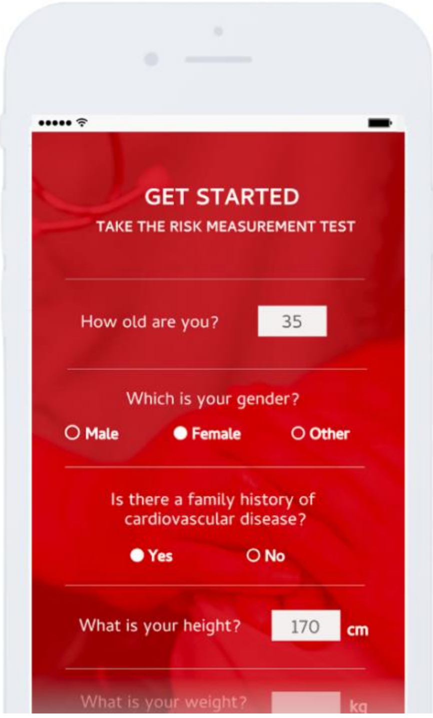
Source: FITVII (n.d.)

3.3.2 Utility

The main objective of Heart Focus is to achieve a greater life expectancy and quality of life for its users through prevention. This goal can not be achieved without the commitment and help of different agents, namely the users/patients themselves, doctors and health institutions.

The first benefit that this mobile application can provide to the *user/patient* is an approximate diagnosis. When users join the application for the first time, they will be asked specific questions about their age, sex and family history, among others, that will allow approximately determining their current state of health with regard to cardiovascular disease, as shown in Figure 14. This assessment will be updated with each data that is entered in the application.

Figure 14: Risk Factor Initial Test



Source: Own elaboration

The second benefit is self-monitoring, which will be completed with automatically collected data and manually entered data. Variables such as heart rate, blood pressure, quality of sleep, steps and calories burned with physical exercise can get automatically measured with a smartwatch. On the other hand, variables such as cholesterol levels, smoking/drinking habits, a poor diet, stress and weight must be entered manually.

The third benefit that has been identified is motivation. Achieving greater independence will help reinforce the patients' willingness to improve their health. The language used in certain sections of the page must maintain an upbeat energy, both to get the users to actively engage with the application and to keep a positive attitude throughout the whole process.

The fourth and final benefit is education. This App provides access to multiple educational videos, articles and books that will help users and patients learn more about heart conditions and also show them how they can take better care of their own health.

From a *medical* point of view, real-time patient tracking is the main benefit provided by this application. By continuously monitoring the health status of each patient, a large amount of data is generated daily, creating the opportunity for better analysis and diagnosis. In addition, an alert system would inform doctors every time an anomaly is detected so they can provide medical care as soon as possible. Another benefit that will affect doctors and health centers will be the reduction of hospital saturation; since Heart Focus will provide chronic cardiovascular disease patients with more independence and create the possibility for doctors to submit online reports to their patients, the number of hospital visits will be greatly reduced.

Lastly, doctors will be able to access to up-to-date information on the latest research findings on cardiovascular diseases. The centralization of these articles will save them search time and improve their field knowledge.

To end this section, we will discuss the benefits that Heart Focus generates for *health institutions* (health centers and government agencies):

- **Prevention and control:** With direct access to the Heart Focus database, health institutions will be able to generate a complete picture of the problem, improving its analysis and providing the necessary information to create the appropriate prevention policies.

- **Emergency management:** Through its alert system, Heart Focus would optimize emergency care by informing health centers about heart strokes, automatically sending the patient's location and sending an ambulance immediately without the need to wait for someone to call or report on what happened. This system would allow the medical team to arrive on time to save the patient's life. This aspect is especially relevant and useful for older people who live alone.

- **Reduction of costs:** The active participation of patients in improving their own health and the ability to provide telemedicine services, will eventually be reflected in the finances of governments, alleviating the financial burden of chronic diseases.

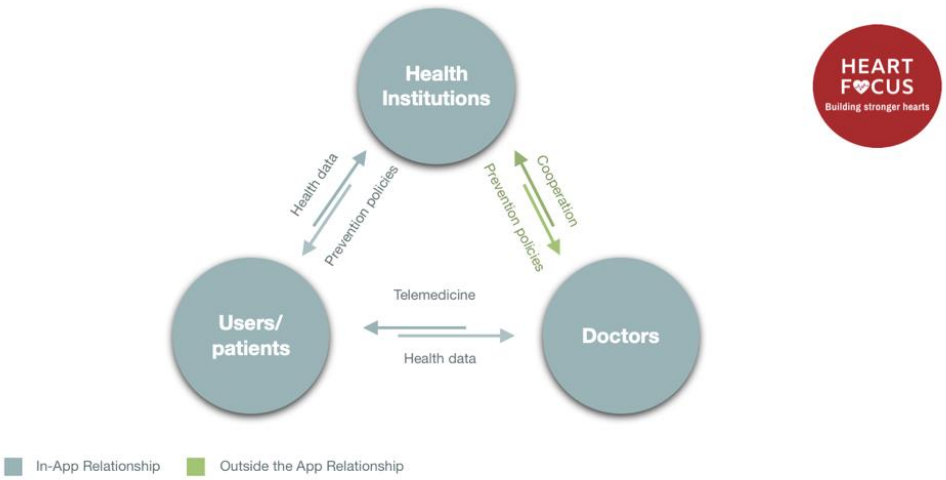
- **Contribution to research:** Large sets of data including many variables will set the basis for relevant research studies, that will eventually improve the prevention of cardiovascular diseases through better management.

3.3.3 Interactivity

Interactivity plays a relevant role in the acceptance of the devices of the future, and an example of that would be Alexa and Google Home, or the development of interactive augmented reality systems that would be implemented in operating rooms.

This mobile application is focused on bringing users/patients, doctors and health institutions closer in the prevention of heart conditions. The interactivity increase generated in three different relationships involved in the prevention of cardiovascular diseases is one of the ideas that makes this App unique and valuable for all the parties involved. It is expected that the existing relationship between health institutions and doctors will be affected as both agents should coordinate and cooperate in the development of prevention policies, but in any case, it is a relationship that would occur outside of the App, and for this will not be further analyzed. In order to simplify the understanding of these relationships, the following scheme has been created.

Figure 15: Scheme of Interaction and Relationships Among Agents Involved



Source: Own elaboration

Health Institution – Patient Relationship

The relationship between health institutions and patients will be partially established directly, through the mobile application, and indirectly, through policy making.

On the one hand, Heart Focus will be responsible for collecting health data from users and generating databases, which will immediately be available for analysis by health institutions in charge of prevention management. In addition, the previously mentioned alert system integrated in the App will keep patients and health centers in contact whenever a patient needs urgent medical care.

On the other hand, government health agencies will indirectly influence patients through the development and execution of prevention plans, that will eventually reflect on patients' health through better care services. Augmented reality applications could be used for research and medical purposes, since they allow to explore a 3D beating heart with a 360º vision and even acces to its internal structure. Researchers would be able to see what happens when increasing or decreasing the beats per minute and go through the entire process of a heart stroke episode while it is being explained through voice and text.

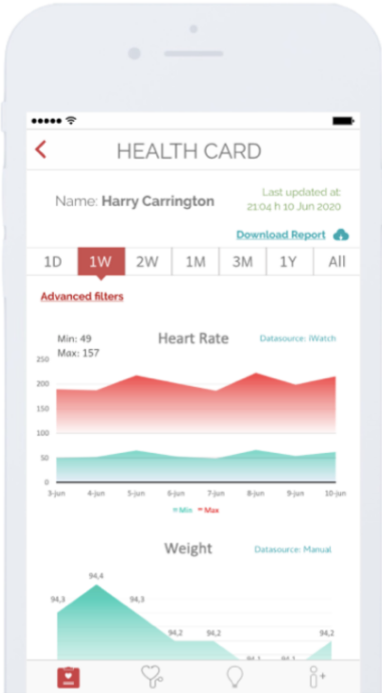
Doctor – Patient Relationship

This is one of the relationships that influences adoption the most, since the participation of doctors in the Heart Focus application generates feelings of confidence and safety in patients that invite them to trust the App and actively engage in their recovery process. Additionally, as it has been mentioned in previous sections, both patient self-care and telemedicine are the key elements that should be reinforced in order to generate high impact changes in reducing the economic cost that long-term diseases generate for governments specifically, and society as a whole.

The doctor – patient interactive relationship will come true through the health data that will be captured by the smartwatches connected to the App and shown to physicians in real time, and the reports that will be automatically created and made available for medical consultation (as shown in Figure 16). In this way, doctors will be able to provide patients with more accurate diagnosis and more effective treatments.

On the other side of this relationship are the recommendations or feedback that physicians can send their patients through the App on their evolution or to inform them about treatment modifications.

Figure 16: Patient Card Example



Source: Own elaboration

3.3.4 Perceived Health Threat and Psychological Pressure

Now we will delve into two psychological factors that influence the acceptance of the Heart Focus App:

- *Perceived Health Threat:* The core target of Heart Focus App are those individuals who are recovering from heart stroke episodes, those with chronic cardiovascular conditions and those who are prone to developing heart disease and want to keep their risk factors in line. The common denominator of these three groups is their fear of heart failure, which will translate into a psychological pressure to pay special attention to their own health and thus be able to prevent this event from happening.

- *Psychological Pressure:* Even though being aware of their health risk is positive for the acceptance of the App, it might as well turn into a psychological pressure for some individuals. This is explained by the patient’s eagerness for recovery, which could result in an excessive use of the application. However, these negative effects can be mitigated with the regular interactions with doctors, a feacture that has also been integrated inside the Heart Focus App.

3.4 Cardiovascular Disease Trend Analysis

To understand the importance of prevention and the development of new technology-supported policies, it is necessary to take a global look at the disease (in this case, cardiovascular disease), to identify present and new trends, and thus be able to effectively anticipate future problems.

As mentioned in previous sections, cardiovascular disease (CVD) is one of the leading causes of death worldwide, and many countries have made efforts to reduce risk factors among its inhabitants. However, the evolution of deaths caused by this type of disease has been different by country; one of the factors that explains the differences in their evolution is their degree of development (although certain countries want to make prevention efforts, they may not have sufficient economic capacity to do so). Figure 17 reflects this reality through data on deaths per 100000 inhabitants from 1990 to 2017, differentiating between countries with a high, middle and low socio-demographic index (SDI), which has been defined by the Institute for Health Metrics and Evaluation (n.d.) as "a summary measure that identifies where countries or other geographic areas sit on the spectrum of development. Expressed on a scale of 0 to 1, SDI is a composite average of the rankings of the incomes per capita, average educational attainment, and fertility rates of all areas"[3].

Figure 17: Deaths Caused by CVD in Low, Middle and High SDI Countries

Source: Own elaboration with data from Institute for Health Metrics and Evaluation (2017)

3 See http://www.healthdata.org/taxonomy/glossary/socio-demographic-index-sdi

As it is deduced from the graph, on the one hand, the countries that have a low SDI show a relatively constant evolution throughout the study period; conversely, the countries with a medium level of development clearly show an upward trend that should be addressed as soon as possible to avoid major problems in the future. On the other hand, highly developed countries present the largest number of deaths out of the three country aggregations, and they have had a favourable evolution in reducing the number of deaths until 2010 approximately; thereafter, the situation worsens, increasing the number of deaths from CVD.

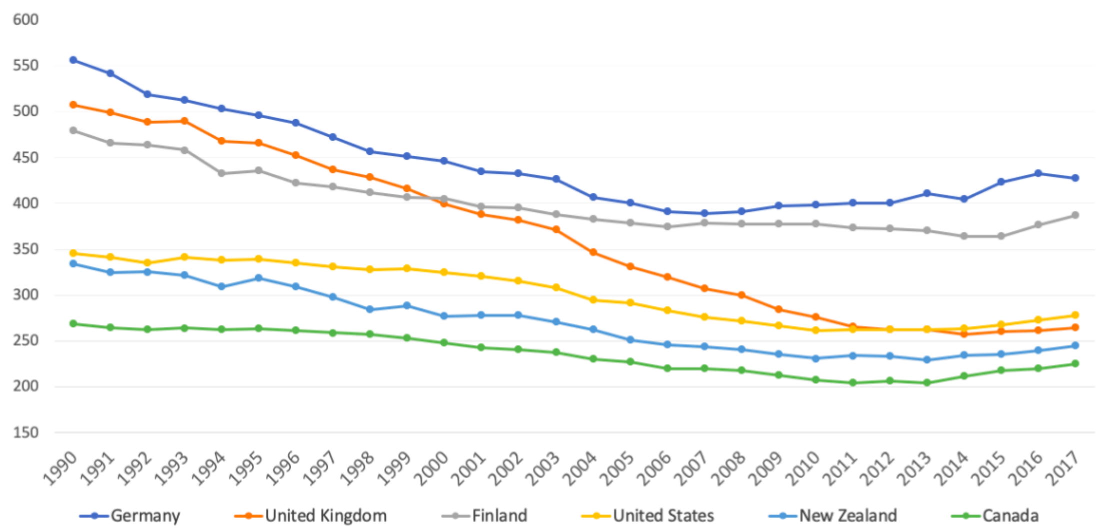
In general, the less developed countries do not have the economic capacity to carry out these prevention efforts; however, despite the fact that developed countries have the economic capacity to face this great health challenge, they still present the highest number of deaths from cardiovascular diseases (even though they have usually carried out prevention efforts), which is mainly due to a sedentary or obese lifestyle, among other habits. In contrast, their level of economic development does allow them, in most cases, to focus on improving the quality of life and thus the health of their citizens. It should be mentioned that, as deaths from CVD increase with the level of economic development, CVD may not be considered a main national health problem in less developed countries.

The next subsections will focus, first on explaining the evolution of the number of deaths caused by CVD in high SDI countries by studying the effects of different CVD prevention initiatives on the reduction of deaths caused by this type of disease in a selection of developed countries and, second, in the correlation between the worrying trend of an increasingly aged population and CVD deaths.

3.4.1 The Effects of Prevention on Deaths Caused by Cardiovascular Disease

In an attempt to reduce the global burden of cardiovascular disease, different prevention efforts have been carried out around the world. In order to check whether there has been a reduction in deaths from cardiovascular diseases in those developed countries where prevention policies have been implemented, six countries from very different areas of the world have been selected; specifically, Germany, United Kingdom, Finland, United States, New Zealand and Canada. The evolution of the rate of deaths caused by cardiovascular disease per 100000 people in each of these countries is shown in Figure 18 below.

Figure 18: Evolution of Deaths Caused by CVD in Germany, United Kingdom, Finland, United States, New Zealand and Canada



Source: Own elaboration with data from Institute for Health Metrics and Evaluation (2017)

As it is observed, on the one hand, Germany, United Kingdom and Finland are the countries that present the highest rate of deaths caused by CVD per 100000 people in the period between 1990 and 2017. However, the UK shows a prominent decline in deaths, outperforming the other countries. On the other hand, United States, New Zealand and Canada show the lowest rate of deaths in the sample period. The rate of deaths caused by CVD per 100000 people shows a clear downward trend for all the countries examined, but from about 2010 onwards (approximately between 2007 and 2015), all of them also show an increase in the ratio. Accounting for this fact, 2010 has been taken as a reference year to carry out the hypothesis test to check whether this change in the trend has actually occurred.

Therefore, we split the sample into two time periods; the first one goes from 1990 to 2009 (20 observations), both included, and the second varies from 2010 to 2017 (8 observations), both included. The analytic tool chosen to analyze these data series has been the hypothesis test for difference of population means, as it is a common procedure to detect changes in the behaviour of a specific variable over time and to compare the behavior of the variables before and after the breakpoint. Specifically, the method used is a t-test for differences between means assuming equal (unknown) population variances. The data needed is obtained from the Institute for Health Metrics and Evaluation, which precisely provides data on deaths caused by cardiovascular diseases per 100000 inhabitants. The results of the tests for differences between population means are presented in Table 6.

Table 6: Results of the Tests for Differences between Population Means for Deaths Caused by Cardiovascular Disease

Cardiovascular disease: Mortality rate before 2010 versus mortality rate after 2010						
	Germany	**United Kingdom**	**Finland**	**United States**	**New Zealand**	**Canada**
Hypothetical difference of the means	0	0	0	0	0	0
Degrees of freedom	26	26	26	26	26	26
T statistic	2,24931	5,44138	3,24449	5,26674	4,34755	4,89218
P(T<=t) one tail	0,01659	0,00001	0,00161	0,00001	0,00009	0,00002
Critical value (one tail)	1,70562	1,70562	1,70562	1,70562	1,70562	1,70562
P(T<=t) two tails	0,03318	0,00001	0,00323	0,00002	0,00019	0,00004
Critical value (two tails)	2,05553	2,05553	2,05553	2,05553	2,05553	2,05553

Source: Own elaboration

The study carried out shows that the means before 2010 are higher than those after 2010, which shows that there has been a reduction of deaths caused by cardiovascular disease, probably due to prevention efforts focused on reducing risk factors. The results of the hypothesis test confirm this change in the trend because the null hypothesis of equality of means before and after 2010 is rejected for all countries, as the t-statistic values are higher than the corresponding critical values (please note that the test statistics are always positive, so we do not reject that $\mu_x > \mu_y$); in other words, p-values are lower than the usual signification levels (even 1%). In addition, p-values are particularly low, involving that the empirical evidence provided is very consistent in showing that there has been a change in the mean in 2010. Thus, our initial belief regarding the choice of 2010 as a breakpoint was confirmed with the results of this test.[4]

In view of the test results, the prevention programs implemented in the countries under study may have had a role in the reduction of the average number of deaths per 100000 inhabitants. In this sense, next we briefly discuss the different approaches adopted by each country.

Germany presents the highest number of deaths for every 100000 people among the countries selected within the period 1990-2017; however, they have managed to

[4] Additional tests were also made so as to consider other years in the 2002-2010 period. Finally, 2010 is selected also regarding the year-on-year variation rates, as it is the first year since 2002 in which the ratio increases for more than one country.

reduce their death rate by CVD in the last 50 years. According to Busse et al. (2010), Germany mainly focuses its prevention policies on individual attitudes towards exercising, smoking and other risk factors. Even though their spending on prevention is higher than the OECD average, some risk factors are still above the average. The OECD (2015) reported that the quality of German primary care is below average, so it recommended to strengthen it to provide better prevention, early diagnosis and management of cardiovascular disease.

The United Kingdom offers a comprehensive approach to prevention, covering leadership and governance, healthcare financing, health workforce, medical products/technologies (including a heart age test and an App), information and research and service delivery (Public Health England, 2018). They have created a national program called the NHS Health Check that offers people aged between 40 and 64 a check-up every five years to early detect signs of heart and kidney disease, diabetes and dementia. The data generated is used to monitor the program and to improve prevention services at a local level adapting them to different risk factors and vulnerable groups. The UK has also designed the Quality and Outcomes Framework (QOF), which rewards general practices for providing quality care to their patients.

In Finland, The North Karelia Project has been developed from 1972 to prevent cardiovascular disease. Vartiainen (2018) explains that its interventions include informational and educational efforts aimed at the general public and population at risk, cooperation with food industries to reduce salt composition of their products, and legislation changes that banned tobacco advertisements among other measures. This project has succeeded in reducing coronary mortality by 84% of the middle-aged population between 1972 and 2014, and has served as an example of prevention for many other countries.

United States is another country that offers an individual approach to prevention according to Busse et al. (2010). Nevetheless, the Centers for Disease Control and Prevention (2020) mentions three programs that have been implemented in the US regarding cardiovascular disease: Division for Heart Disease and Stroke Prevention (DHDSP) funds state and local health departments to provide additional guidance and support in heart disease and stroke prevention; Million Hearts aims to prevent 1 million heart attacks and strokes within 5 years by focusing a few concrete targets; and WISEWOMAN, that helps low-income, uninsured and underinsured women aged between 40 and 64 to detect and prevent heart disease and stroke risk factors, as well as to promote healthy lifestyles.

New Zealand and Canada are two countries that also offer an integrated approach to CVD prevention. In the first case, the Ministry of Health in New Zealand (n.d.) has published several guidelines based on the latest available evidence for health practitioners to inform people about how to reduce the risk of developing cardiovascular conditions and to improve their health and wellbeing. In addition, an Integrated Diabetes Service was established in 2011 to better coordinate primary and secondary care. Moreover, they are currently improving the management of CVD by performing earlier screenings, specifically starting at age 30 years for men and age 40 years for women (Heart Foundation, 2018).

In Canada, prevention efforts target the self-management of people at risk by informing them about how to improve their nutrition and physical health, as well as monitoring heart diseases and conditions at a government level using provincial and territorial health data from the Canadian Chronic Disease Surveillance System (Government of Canada, 2017).

Despite the fact that the prevention efforts implemented in all these countries have had a positive effect on controlling risk factors since 1990, the number of deaths caused by cardiovascular conditions in the countries under study also show an upward trend in the last 10 years – evidenced by positive annual variations from 2010 – regardless of being located in very different parts of the world (see Figure 18). This suggests that there could be some underlying global effect that could generate this change in the trend, an issue to be analyzed in the next section.

3.4.2 The Implications of Aging in Developed Countries

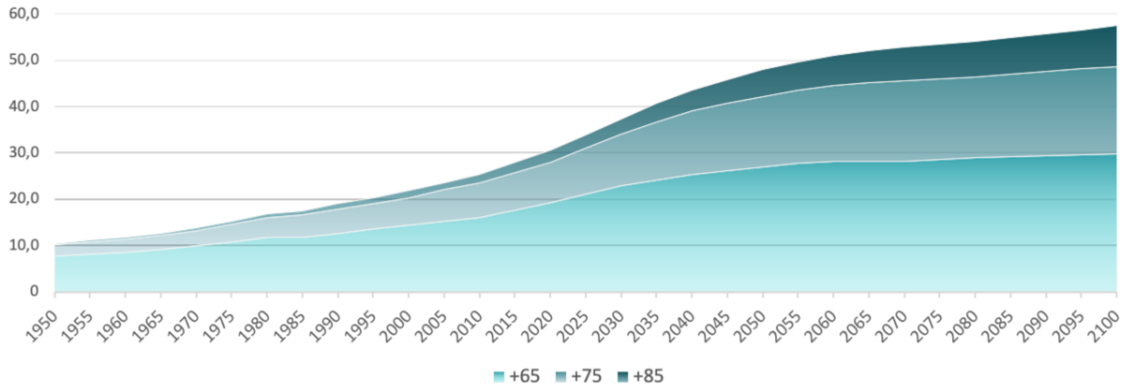
After consulting data on deaths from cardiovascular diseases in some countries beyond those included in this study, we evidence that the increase in CVD mortality is an uptrend that affects developed countries in all areas of the world (which can also be seen in Figure 17) despite the implementation of prevention policies, this fact suggests that this problem may have to do with non-modifiable factors, instead of modifiable ones. A study about the demographic and epidemiologic drivers of global cardiovascular mortality conducted by Roth et al. (2015) showed that, between 1990 and 2013, 55%

increase in mortality from cardiovascular disease was caused by the aging of the population, and 25% was due to population growth. These results suggest a moderate or even strong correlation between aging and increased deaths from cardiovascular disease.

However, this is not just an issue for that particular period, but a trend that threatens the health of the elderly and that also has important consequences for the financial sustainability of the health sector (e.g., with the emergence of chronic conditions), and even for the State finances or the labour market. Moreover, the fact that the cause of this trend is a risk factor that cannot be changed forces the competent authorities to implement new management systems, financial plans and prevention policies in order to reduce as much as possible the risk that this situation entails. In this subsection, the focus will be on population aging, since, as explained above, it is a global problem that has major social and economic implications.

To highlight the severity of this problem, the United Nations database containing world demographics has been accessed. The World Population Prospects 2019 by United Nations show real data from 1950 to 2019, and the future demographic prospects until 2100. The United Nations database offers region aggregations such as high, middle and low-income countries, continent aggregations and groups according to the state of development of the countries. So as to give an overall picture of the situation in the countries under study, we have selected the data corresponding to the most developed regions aggregation. Figure 19 shows the percentage of the total population that are over 65, 75 and 85 years in developed countries.

Figure 19: Percentage of Population over 65, 75 and 85 Years in More Developed Regions



Source: Own elaboration from United Nations (2019)

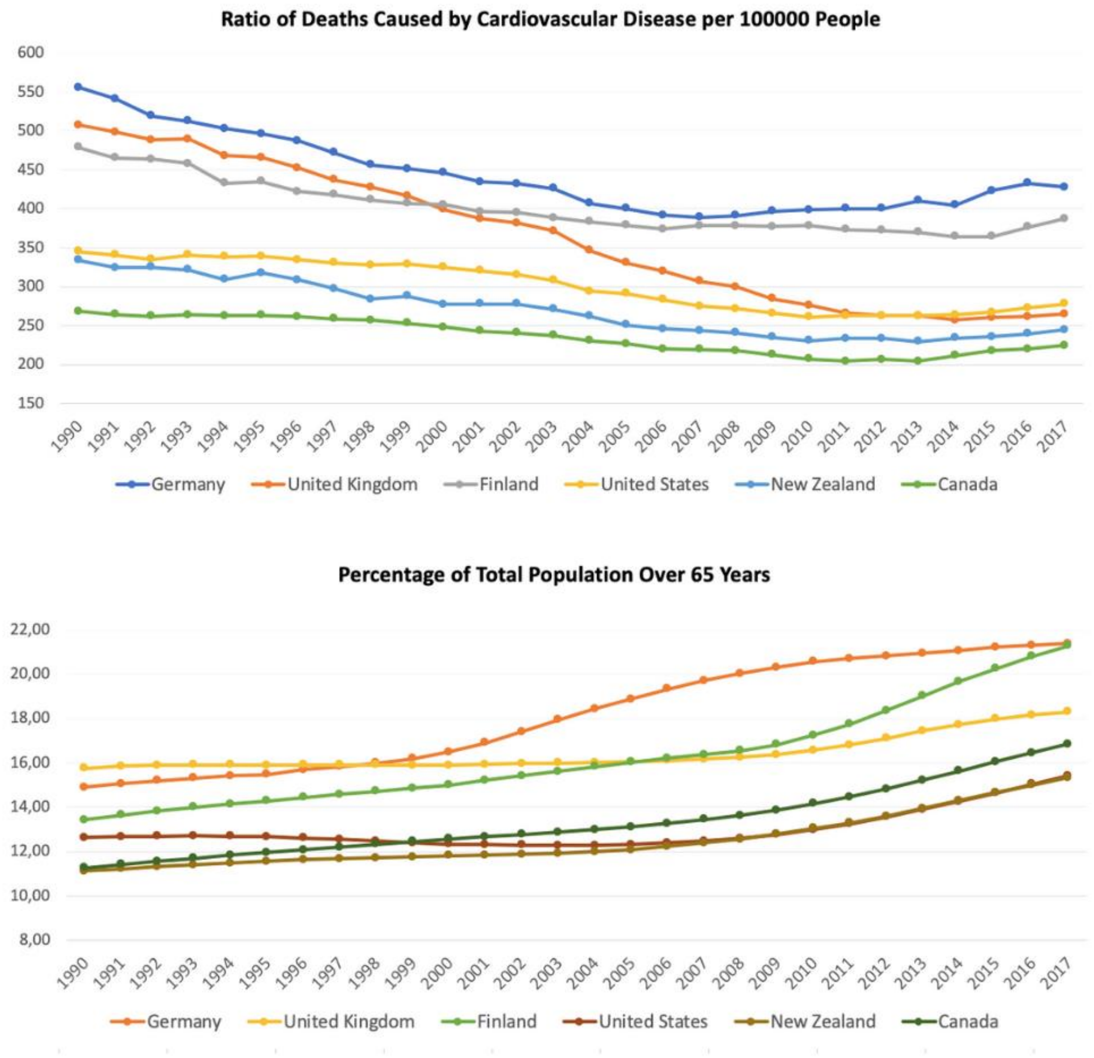
Firstly, the percentage of population over 65 years has ranged among 7,7% and 16,0% in 1950-2010, however the growth of this proportion is expected to considerably accelerate in the next 30 years, showing the largest five-year increase in 2020 (9,8%), and therefore rising from a 16,0% to a 25,3% in a relatively short time frame. Secondly, regarding population over 75 years, this acceleration happens 10 years later, going from values among 2,4% and 8,7% from 1950 to 2020, to an expected rise from 8,7% to 14,6% in the next 25 years, displaying the largest five-year increase in 2025 (13,5%). Lastly, the percentage of population over 85 years goes from a 0,3% in 1950 to an expected 3,2% in 2030, reaching the highest five-year increase in 2010 (24,3%). The acceleration of the oldest of the three age groups we have considered happens 10 years later than for population over 75 years (i.e., in 2030), when the percentage rises from 3,2% to 5,7% in 20 years.

From these figures it can be deduced that the aging of the population is expected to be more pronounced and take place faster over time. Likewise, these expectations of a strong increase in the elderly population reveal that it will be essential to reinforce prevention to minimize the impact of aging on the deaths caused by cardiovascular disease. Besides that, we must wait to discover how the COVID-19 pandemic will affect possible forecasts on this topic.

3.4.3 The Relationship between Aging and Deaths from Cardiovascular Disease

With the purpose of finding out a potential relationship between the increase in deaths caused by cardiovascular disease in recent years and the aging of the population, a correlation analysis has been performed for each country under study. For the data on deaths (ratio of deaths caused by cardiovascular disease per 100000 people), the Institute for Health Metrics and Evaluation (2017) source has been used, and for the data on aging (percentage of total population over 65 years), the World Bank (2019) source has been accessed because it offers annual data, instead of every five years. Figure 20 compares the evolution of both time series.

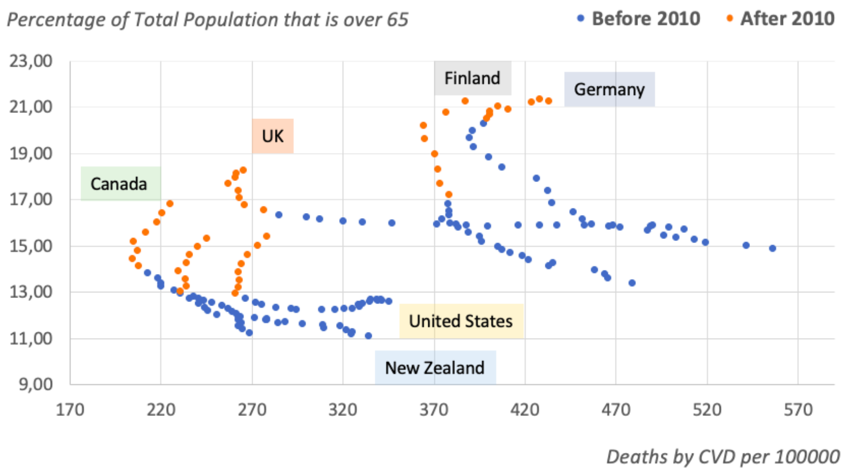
Figure 20: Comparison of Deaths by CVD and +65 Population



Source: Own elaboration

As we observe from the previous figure, the relationship between the ratio of death caused by CVD and the percentage of population over 65 years seems clearly negative, as deaths globally decrease (except for the last couple of years) and the percentage of population over 65 increases over time. In order to visualize more clearly the relationship between the two variables, a scatter plot has also been made (see Figure 21). In addition, data for the period prior to 2010 and the period from 2010 onwards have been separated by colour, concluding that the relationship is negative before 2010 and positive thereafter.

Figure 21: Relationship between CVD and +65 Population Before and After 2010



Source: Own elaboration

As the previous figures only give a preliminar idea on the relationship, we carry out a correlation analysis. Table 7 shows the results of this analysis by using the Pearson's r, where we have considered both the whole sample and its division in two time periods; the first one goes from 1990 to 2009, and the second goes from 2010 to 2017. The choice of the year 2010 as the turning point is due to the fact that it is the year we have tested in section 3.4.1 for a change in the trend of CVD deaths; furthermore, it appears that from this year onwards the proportion of the elderly population is increasing at a faster rate (see Figure 19). Even so, we should take the results of the correlation analysis after 2010 with caution since it refers to a period for which we have a very limited amount of data.

Table 7: Results of the Correlation Analysis by Country (values for *r*)

	TOTAL	< 2010	> 2010
Germany	-0,8373	-0,9255	0,9122
United Kingdom	-0,7582	-0,8785	-0,6457
Finland	-0,7591	-0,9492	0,1652
United States	-0,5369	0,2716	0,9183
New Zealand	-0,7747	-0,9590	0,8311
Canada	-0,8163	-0,9666	0,9193

Source: Own elaboration

The results of the correlation test confirm that the relationship between the two variables considering the whole sample is clearly negative, as the value of the correlation coefficient is negative for all countries, showing values that are overall close to -1 (then, the two variables show a moderate or even strong linear dependence). Regarding the results of splitting the sample, on the one hand, we identify that in the period from 1990 to 2009, the correlation coefficients are negative, evidencing a negative relationship between the percentage of the aged population and the deaths from cardiovascular diseases. This suggests that most countries have managed to reduce deaths through prevention despite the aging of the population. However, United States shows a positive correlation coefficient, showing a descending number of people over 65 during the 90s. A study conducted by Sengupta et al. (2005) on population over 65 in the United States explains this difference by higher immigration and higher fertility levels than in other developed countries.

On the other hand, for the period ranging from 2010 to 2017, the results show positive correlation coefficients, indicating a direct and positive relationship between both variables for almost all countries. Furthermore, these values are quite close to 1, indicating a strong correlation that, taking into account the demographic forecasts elaborated by the United Nations, would confirm an upward trend that endangers the lives of our elderly, the sustainability of the health system and the finances of the countries involved.

However, this second analysis shows surprising results for Finland and the United Kingdom. Firstly, a low positive value of the correlation coefficient for Finland could be explained by high quality aging. Its major prevention efforts since 1972 have led to a large decrease in CVD deaths, which is mainly due to a reduction in risk factors (Vartiainen, 2018), which in turn translates into a large improvement in the health of its inhabitants and an increase in life expectancy. Secondly, the large reduction in cardiovascular disease deaths in the United Kingdom is very slightly altered by an increase in the period between 2015 and 2017. However, this increase is not strong enough to reverse the relationship between the two variables under study. As aforementioned, the sample is too short in the second period, so all these resuls should be taken with caution.

In conclusion, the correlation analysis carried out shows that the worrying phenomenon of an aging population and deaths from cardiovascular disease are linked, even moderately for the majority of the sample. This fact underlines the importance of strengthening prevention and taking advantage of all the benefits offered by new technologies to improve the quality of life and health of an increasingly aging population, and to avoid the saturation of the health system and the imbalance of the State finances.

Conclusions

The most advanced technology has already reached our homes, but it is not yet fully present in key sectors such as health. The arrival of artificial intelligence (AI), wearable health devices (WHD), mass data analysis and augmented reality (AR), among others, is boosting the development of the potential that these technologies offer. The objectives of this bachelor's thesis are two: to review the literature on the acceptance and use of technology in healthcare, and to develop the Heart Focus application, which would serve not only to improve the cardiovascular health of patients but also to provide information and big data to health centers and other management units supporting health authorities.

The Heart Focus App is divided in two sections. First, the mobile application is devised through the combination of wearable health devices and big data analysis technology, aiming to prevent heart and cardiovascular diseases (CVD) from three different levels (user/patient, medical and institutional). Then, a statistical study has been conducted to better understand the dynamics and magnitude of cardiovascular disease, by taking a global look at it and identifying present and new trends in a sample of countries that have implemented prevention policies on CVD; these countries are Germany, Finland, United Kingdom, United States, New Zealand and Canada, and the period under study goes from 1990 to 2017.

Firstly, from the literature review it has been extracted that the main acceptance factors to be enhanced are perceived utility and ease of use in WHD, also attitude towards technology in applications for chronic disease; trust, usage value and interactivity in AR applications, and the reduction of privacy risk in AI applications. In addition, it has unveiled how big data analysis can help to optimize health services and to prevent the health and financial impact of chronic diseases through personalized analysis and preventive interventions.

Secondly, from the findings of the literature review, the adoption of Heart Focus App has been strengthened though ease of use, with a simple and consistent design; utility, with benefits for patients, doctors and institutions; interactivity, through the connection of different agents through the App; and also studied the effects of psychological pressure and perceived health risk. The joint study of user psychology, technology and information management through the development of an app that integrates the functionalities of those existing in the market, has helped me to understand the great power and potential of the combination of these disciplines for the transformation of society and the economy (e.g., electronic banking for the elderly).

Thirdly, in order to detect existing and new trends in CVD we conducted a hypothesis test, which has shown that there has been a change in the trend of cardiovascular disease deaths in 2010, showing a reduction in developed countries that have made prevention efforts. Moreover, based on the correlation analysis carried out, there is a remarkable association between the increase in deaths from cardiovascular diseases from 2010 onwards and a greater aging of the population.

It therefore follows that, as the aging population threatens the sustainability of the health system and the State finances, prevention efforts will be essential to alleviate this burden. For this reason, governments, R+D+I agents, health institutions, doctors and users/patients must cooperate to save lives by integrating new technologies into their interventions in order to achieve an unprecedented impact on health, society and the economy.

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