HOW EMPLOYEES ACCEPT ROBOTS AT WORK

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UNIVERSITAT ROVIRA i VIRGILI

How employees accept robots at work

JUAN ANDRÉS MONTERO VILELA

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"HOW EMPLOYEES ACCEPT ROBOTS AT WORK"

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FAIG CONSTAR que aquest treball, titulat "**How employees accept robots at work**", que presenta **Don Juan Andrés Montero Vilela** per a l'obtenció del títol de Doctor, ha estat realitzat sota la meva direcció al Departament de Gestió d'empreses d'aquesta universitat, complint amb tots els requeriments per a rebre la menció Doctorat Internacional.

HACEMOS CONSTAR que el presente trabajo, titulado "**How employees accept robots at work**", que presenta **Don Juan Andrés Montero Vilela** para la obtención del título de Doctor, ha sido realizado bajo mi dirección en el Departamento de Gestión de Empresas de esta universidad, cumpliendo con todos los requisitos para recibir la mención Doctorado Internacional.

WE STATE that the present study, entitled "**How employees accept robots at work**", presented by **Mr. Juan Andrés Montero Vilela** for the degree of Ph.D., has been carried out under my supervision at the Department Business Management of this university, and that it fulfils all the requirements to receive the International Doctorate Distinction.

Tarragona, 23 d'agost de 2023 / Tarragona, 23 de agosto de 2023 / Tarragona, August 23rd, 2023

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Mario Arias Oliva	**Jorge Pelegrín Borondo**	**Jorge de Andrés Sánchez**

To my parents, who will be always on my mind.

A mis padres, que permanecerán siempre en mi memoria.

HOW EMPLOYEES ACCEPT ROBOTS AT WORK

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Universitat Rovira i Virgili
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Juan A. Montero Vilela
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List of Abbreviations

AI	Artificial Intelligence.
ALFUS	Autonomy Levels for Unmanned Systems.
AMT	Advanced Manufacturing Technology.
BANI	Brittle, Anxious, Non-linear and Incomprehensible.
BI	Behavioral Intention.
BPA	Business Process Automation.
CAN	Cognitive Affective Normative Model.
COBOT	Collaborative robot.
CSCW	Computer-Supported Cooperative Work.
CSR	Collaborative Service Robots
CSR	Corporate Social Responsibility.
CX	Customer experience.
DTPB	Decomposed Theory of Planned Behavior.
EOAT	End of arm tooling.
IMF	International Monetary Fund.
GM	General Manager.
HRCS	Human-Robot Collaboration Systems.
HRI	Human-Robot Interaction.
IA	Intelligent Augmentation (also named I. Automation, I. Amplification, Assistive Intelligence, Cognitive Automation, Cognitive Augmentation, or Machine Augmented Intelligence).
ICT	Information and communication technologies.
IFR	International Federation of Robotics.
IPA	Intelligence Process Automation.
IRC	Internet Relay Chat.
KOL	Key Opinion Leader.
LARs	Lethal Autonomous Robots.
LAWs	Lethal Autonomous Weapons.
MNC	Multinational Company.
MPCU	Model Personal Computer Use.
OT/ICS	Operational Technology/ Industrial Control Systems.
PbD	Programming by Demonstration.
RaaS	Robotization as a Service.
RBV	Resource-based view theory.
RCS	Robot control system.
RPA	Robotic Process Automation.
RAW	Robot Acceptance at Work
SDG	Sustainable Development Goals.
SME	Small and Medium Enterprises.

STEM	Science, Technology, Engineering and Mathematics.
TAM	Technology Acceptance Model.
TPB	Theory of Planned Behavior.
UB	Use Behavior.
UX	User experience.
UTAUT	Unified Theory of Acceptance and Use of Technology.
VUCA	Volatility, Uncertainty, Complexity and Ambiguity.
WEF	World Economic Forum.
WTC	Willingness To Collaborate.

Abstract

This research analyzes the acceptance of robotics at work by employees. Robotization represents an opportunity for companies to improve their overall performance. However, this automation process may represent a challenge if it is not properly integrated within the organization and if potential risks are not minimized. In relation to the general trend towards automation, there are external and internal conditions that organizations need to manage simultaneously in accordance with their stakeholders' expectations. This research considers employees both as users of these robots at work and as key stakeholders to shed light on how to manage robotization most effectively, from an organizational perspective. Based on the CAN Model, this research provides additional input about the acceptance of robots at work. For this purpose, data from 422 participants from different geographies, wide range of profiles and from numerous industries have been collected. The findings from this research confirmed elements of the CAN model, showing that employee's attitude has a positive relationship with the intention to work with robots, and that attitude is positively influenced by the Performance Expectancy, Perceived Risk and Positive Emotions of employees. Based on these findings, in addition, it has been addressed an analysis, to determine implications on innovation, workplace and performance management. According to these findings, some high-level recommendations for managers, researchers and other stakeholders are shared in an attempt to illustrate that organizations should address specific managerial strategies to gain greater acceptance by employees regarding the implementation of robotization, which should be translated into employee's attraction, retention, and engagement.

Keywords: Robot acceptance at work; Human-robot interaction; Robotics; CAN Model

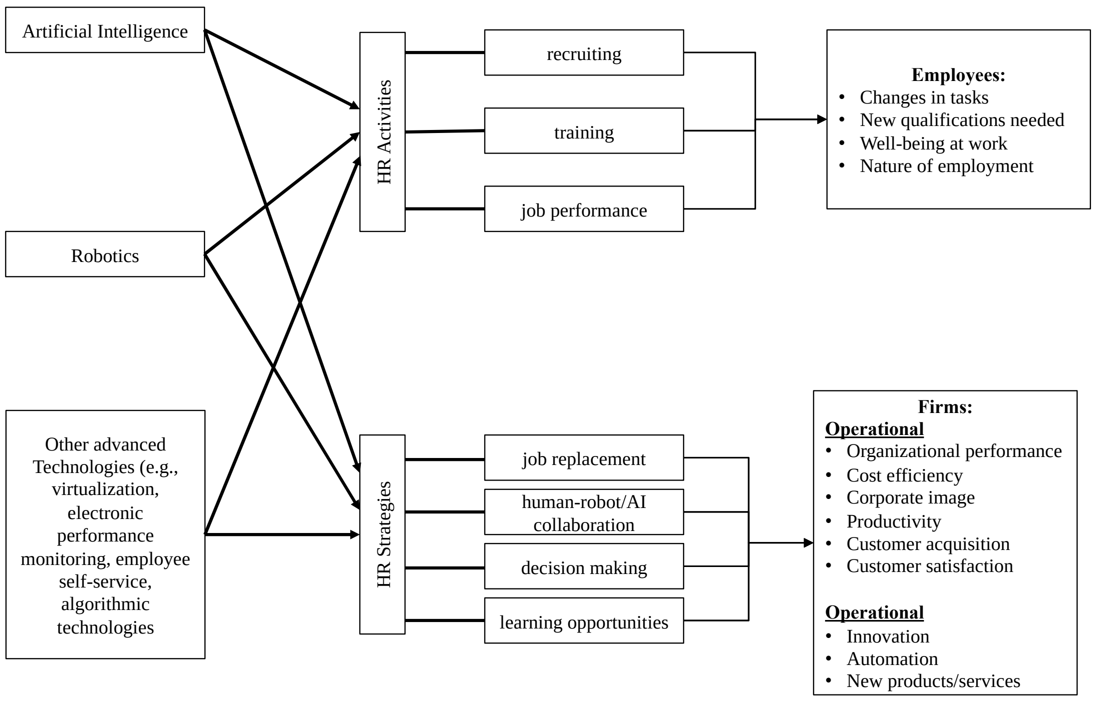
CHAPTER 1. INTRODUCTION

Beyond their industrial and technological contributions since the 1970s, robots are now able to recognize voices, develop and recognize biometric dimensions, perceive emotions, interpret speech patterns and gestures, and even make eye contact. Indeed, our everyday life is already shared with droid friends and assistants that conduct all manner of tasks and that are being increasingly used, for example, to care for the elderly (Sharkey & Sharkey, 2012), support court decisions (Barona Vilar, 2022; Zeros, 2022), search and rescue people (Hochschule Augsburg, 2023), and educate our children (Reich-Stiebert & Eyssel, 2016; Wu, X. & Gao, 2011). Artificial Intelligence and robotization helped decisively to accelerate the development of drugs and vaccines against covid-19 (ABB Robotics, 2021; Murphy et al., 2020) and has even generated a wide range of literature and academic content with different levels of complexity (Sarker et al., 2021). Artificial Intelligence has generated new and diverse content relatively accurately in a wide range of fields of expertise (Xu et al., 2021). Nonetheless, content generation can be beneficial and accurate to some extent. However, there is no absolute assurance of its accuracy, as demonstrated in this thesis through the experiment, asking to an artificial intelligence software (ChatGPT), to produce a summary based on this dissertation's keywords.

After examining its content (Annex 1), it becomes evident that robotics (artificial intelligence) has managed to construct specific information and weave it together to produce a coherent response. However, while this response may be deemed satisfactory, a closer scrutiny from an advanced academic standpoint might reveal inaccuracies and unverified assumptions. It's worth noting that this inquiry was conducted on April 4, 2023, and if the same question were to be posed again, the response would likely differ, potentially becoming more precise or comprehensive.

Moving forward with the theme of this dissertation, it has already been confirmed that the nature of jobs and the experiences of employees are strongly influenced by Information and Communication Technologies (Wang, B., Liu, & Parker, 2020). We can now therefore consider how technologies related to intelligent automation also impact organizations (Vrontis et al., 2022). These transformations require Human Resources Management to meet certain challenges from the organizational, technological, people management and ethical perspectives (Abney & Bekey, 2012; Chun, R., 2006; Coldwell et al., 2008), that have implications for multiple areas of the company from both the individual and company perspectives (Figure 1.1).

Figure 1.1 Summary of a literature review of Automation Intelligence and HR



Source: Vrontis et al. (2022)

Clearly, more than one approach to analyze the impact of technology on work exists. These approaches include those outlined by (Orlikowski & Scott, 2008) as well as

(Pishdad et al., 2012): the technocentric, the humancentric and the Institutionalisation as shown in table below.

Table 1.1 Perspectives on the role of technology in organizations

Approaches	Authors
Techno-centric perspective: technology as having a deterministic role in predicting changes in organizations.	Dewett & Jones, 2001 Huber, 1990
Human-centric perspective: technology use and its effects to become product of social construction.	Barley, 1988 Zammuto et al., 2007
Technology institutionalisation: there are various sub institutions operating in the organization: organizational culture, social structure, and competitive environment. They mutually interact and the organization establishes its legitimacy.	DiMaggio & Powell, 1983 Powell & DiMaggio, 1991 Delmestri, 2007 Greenwood, 2008

Source: Own development based on Orlikowski & Scott (2008); Pishdad et al. (2012).

These perspectives provide different elements to understand better the context, but we should try to be focused on the specific topic of this research. Beyond the social, organizational, and managerial perspective, automation systems require qualified professionals with specific expectations and needs. In this new context, attention must be paid to several aspects, including: **(1)** employees should be considered key company assets (Ulrich & Smallwood, 2005); and **(2)** employee collaboration with technology is key to a company's success (Huang & Rust, 2017) because employees may, for example, accept or reject technology (Davis et al., 1989), which has a clear impact on the company's strategic decisions regarding robotization and automation. This research has been developed to provide useful insights for organizations and to support the processes aimed at minimizing the negative impacts on organizational performance. It also contributes to academia by providing a better understanding of how employees can impact company performance from an organizational perspective (Manzoor, 2012) and in terms of the projection of company's perception (Glavas & Radic, 2019; Gray & Balmer, 1998).

To understand the overall picture when discussing technology or general automation, we must distinguish between two important concepts: adoption of technology and subsequent acceptance of that technology (Lai, 2017). Although technology adoption and acceptance are related, they are not the same thing since a technology may be widely adopted but not fully accepted. For example, people may use a technology because they feel they have no choice or because it is required for their job (Hwang et al., 2016), but they may not actually enjoy using it. Similarly, a technology may be widely accepted but not fully adopted. For example, people may understand the benefits of a new technology but still hesitate to invest the time and resources needed to fully integrate it into their daily lives or work practices (Jacobs et al., 2019).

Adoption refers to the stage at which an organization decides to use a certain technology. This includes a phase of exploration, research, deliberation, and decision-making before the new system or technology is introduced. This phase is usually led at the corporate, division, or departmental level (Jünger & Mietzner, 2020). The adoption stage is when the company should consider the appropriateness of the decision and even analyze its potential impact on managerial and organizational aspects (Tidd & Thuriaux-Alemán, 2016). Acceptance, on the other hand, refers to changes at the employee (as user) level in terms of attitudes (Imran, 2009), perceptions and actions that lead them to try new practices, activities or innovations that differ from their previous routines or behaviors (Kaldi et al., 2008). This research focuses on this acceptance stage, with the aim of supporting the adoption stage from the employees' perspective, to foresee its potential impact on the organization. The conclusions of this thesis will provide organizations with guidelines on how to adopt robotization initiatives.

The way a company carries out a robotization initiative can therefore be determined by its global strategy factors (Garsombke & Garsombke, 1989), some of which are environmental and transaction-specific; been a complex decision that it goes beyond changing processes or company assets (Kim et al., 2022). Since decisions taken in one geographical area can have repercussions in another (Kim, C. W. & Hwang, 1992), and since we are living in a social world in which a reputation becomes a social perception that can very quickly lead to an action at any distance and time, reputation must be considered one of the most important strategic resources of any company (Flanagan & O'Shaughnessy, 2005; Hall, 1992; Hall, 1993). Of course, those factors or risks related to robotization that may have an impact on the overall organization must also be taken into account (Bergh et al., 2010).

The remainder dissertation is structured as follows:

Table 1.2 Scheme of the dissertation

Introduction	**Theoretical framework**	**Methodology & proposed model**	**Results & conclusions**
Context Relevance Objectives	Robots Robotization & acceptance Technology Acceptance models	Literature Data analysis Proposed model	Unit of analysis Data gathering Descriptive analysis General conclusions Implications and future research Limitations

Source: Own development

1.1 Background and rationale

Revolutions currently taking place at work, in society at large, and in business models require the best adoption of robots and digital technologies. The advantages of robotization for business are obvious: greater efficiency, faster processing, fewer mistakes, lower expenses, etc., etc. However, we cannot forget that value creation in these fast-changing environments depends mainly on improving internal technological, organizational and managerial processes (Teece et al., 1997).

With these kinds of transformations, the advantages for employees and managers are often not so obvious (Hollon & Rogol, 1985; Marangunić & Granić, 2015). Moreover, transcending robotization at work, fear may be sparked by uncertainty regarding how technology will affect society in the future (Lin et al., 2011; Weiss et al., 2011), especially in times like the present when there is so much disruption.

If not properly managed, this fear causes major organizational resistance to change (Dent & Goldberg, 1999). When faced with uncertainty, people naturally cling to what they know. Moreover, it is common for agents of change to ignore the effects of their actions (Jeffrey et al., 2008).

Under the new context of Industry 5.0, which is intended to pursue a more sustainable, human-centric and resilient society (Breque et al., 2021), and since the overall goal of organizations is now to create teams that merge humans and robots to take advantage of both and to generate synergistic cyber forces, how organizations are designed and how we work are becoming crucial. Readiness for an organizational change or innovation, requires mindsets in which the demands for the innovation, change, or new task would be perceived as agreeable (Frese & Zapf, 1994), while most organizational changes have failed because the psychological principles and drivers of change have not been observed or have been violated (Winum et al., 1997). And this failure to execute has become a major reason why many companies are not reaping the expected benefits of innovation (Klein & Sorra, 1996).

This dissertation attempts to answer, at least partially, *how companies can increase their employees' acceptance of the robotization at work*. To do so, it will be analyzed the acceptance of robotization by employees under the CAN model, understanding employees as key stakeholders (Hall, 1992) who become decisive for the implementation of innovation (Schaarschmidt, 2016) to identify key aspects of the robotization process when observed through the lens of those employees. It is also attempt to determine which are the elements that organizations should consider before, during and after robotization, digitization or automation initiatives in order to achieve employee engagement and proper organizational transformation.

To understand the elements and implications of the so-called "Fifth Industrial Revolution", the aims of this research are to obtain the employees' opinions and feelings in order to facilitate interpretative keys of the current momentum and manage key assets such as innovation capabilities to provide new insights into the role that organizations can play in this new context of Industry 5.0. This research does not address whether the robotization process is performing well or to find the best alternative but to understand how employee reluctance or acceptance of robotization, may determine as well the perception of stakeholders and society in general (Freeman, 1984).

Beyond that, could there be a risk to a company's image caused by a decision on robotization? Literature on this matter is analyzed in this dissertation. For instance, layoffs have an important effect on corporate reputation (Flanagan & O'Shaughnessy, 2005) and any negative impact on reputation may be important for a company's business and financial performance (Barney, 1991).

1.2 Relevance

Although robots have been present in companies for decades, companies are now engaged in a constant transformation in terms of business models, technology and organization (Autor, 2015). The most innovative companies want to be the first to integrate the state of the art when it comes to technology (including robotization) into their business model (Huarng et al., 2018), while also paying attention to the role of employee (Marler et al., 2006), since a greater acceptance of robots at work helps to improve important aspects such as efficiency and productivity (Çiğdem et al., 2023).

Robotization means change (Vermeulen et al., 2018) but it has been shown since the last century that employee resistance to change is the main reason why organizational changes fail (Deloitte & Touche, 1996; Prochaska et al., 2001; Marler & Dulebohn, 2005). Recent research also suggests that employee acceptance and collaboration with implemented technology is a determinant of an organization's success and that factors behind employee acceptance can disrupt operations and the integration of technology (Huang & Rust, 2017; Çiğdem et al., 2023). Although robotization was initially conceived in the industrial field, in recent years much research has also taken place in the service sector (Turja & Oksanen, 2019) and has been based on the continuous replacement of human labor by technology (Collins, 2013; Ford, 2015; Borjas & Freeman, 2019; Acemoglu & Restrepo, 2019; Acemoglu & Restrepo, 2020; Parolin, 2021).

Working with people, like working for people, requires *a priori* acceptance (Weng et al., 2009). It is therefore important to identify which factors enable and reduce the willingness of employees to collaborate with robots.

Just as one of the main challenges for current businesses is knowing how to combine the physical and virtual worlds (Tao & Zhang, 2017), organizations also need to be able to converge the human and robotic labor forces. Since new technologies and robotization are invigorating the current VUCA and the more recent BANI contexts, companies must be prepared to avoid any negative impacts this transformation may generate on their operations.

It is important that organizations should be able to take decisions and to promote and manage their change to compete efficiently while also adopting technologies and reducing, as far as possible, inferences and risks in terms of productivity (Van Reenen, 2020), image (Shenkar & Yuchtman-Yaar, 1997) and corporate reputation (Helm, 2011). A successful case is ING, an online bank that has managed to attract roughly 2.5 million clients in Spain. According to the "Informe sobre Reputación Banca España 2018" (Brand Finance, 2018), despite being the most automated bank and a pioneer in terms of digital transformation, ING became, almost without physical presence, the bank with the best reputation in Spain, and followed by competitors like BBVA and Santander. Nowadays, these entities, like other large corporations in Spain, have decisively opted recently for automation and digital transformation (Montero-Vilela et al., 2019). In that sense, and despite the evident employment reduction in the Spanish banking sector, with a 36% of employees' decrease from 2010 until 2021 (Statista, 2022), with a logic negative image and perception by stakeholders (Flanagan & O'Shaughnessy, 2005), proper CSR policies together with expected profitability for shareholders, have compensated that negative effect in terms of overall perception of those financial entities (Rangel-Pérez et al., 2023).

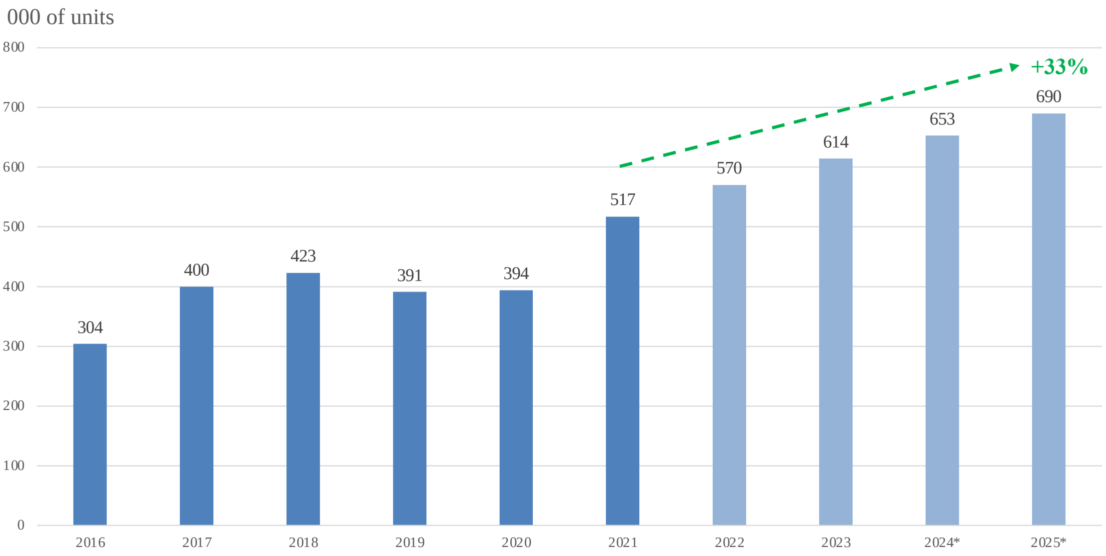
A positive perception of a company is vital for businesses because for instance, robotization (main element of this dissertation) impacts directly or indirectly, over most of the stakeholders: employees, customers, suppliers, shareholders and society (Kim, Y. et al., 2022), influencing consumer behavior, delivering on customer expectations can enhance reputation through a positive word-of-mouth and customer loyalty (Nguyen & Leblanc, 2001), attract, retain talent and build trust (Harvey & Morris, 2012). On the opposite, a negative company's perception can lead to the loss of clients, difficulty attracting talent, lower shareholder value, and potential legal or regulatory challenges

(Brammer & Pavelin, 2006; Rhee & Valdez, 2009).

Although the main objective of this research is framed within the acceptance of robotics by employees, the relevance of this technology acceptance on other indirect aspects like corporate reputation cannot be ignored (Hasija & Esper, 2022). The companies have been rated for decades in terms of reputation, creating a projection, and influencing the evaluations of companies by consumers and specialists (Fombrun, 2007), employees (Turban & Greening, 1997), and investors (Roberts & Dowling, 2002; Srivastava et al., 1997). For these reasons, the link between robotization and stakeholders deserve a minimum context.

Having evolved from its manufacturing implications in the 80s, the impact of automation and robotics on the general economy are becoming evident today – even in service activities such as consultancy, venture capital, education, or transportation. This conclusion is based on monographic reports (Chui et al., 2016; International Federation of Robotics, 2021), and the worldwide turnover linked to Industry 4.0 (including software, peripheral devices and systems engineering), that in 2016 already represented 32,000 million dollars (International Federation of Robotics, 2018).

Figure 1.2 Annual installations of industrial robots 2016-2025



(*) **2023-2024 forecast**

Source: International Federation of Robotics (2022).

We should also bear in mind, however, that the covid-19 pandemic heavily impacted the final number of installations (Figure 1.2). From the business perspective, the health crisis represented a challenge for investment but at the same time showed how decisive robotization can become in such situations (Murphy et al., 2020), especially in industrial environments (International Federation of Robotics, 2021). Of course, it will depend on each industry, or even each company and its resilience to decide whether robotization is key to ensure continuity for its operations in future if another global lockdown would occur (United Nations Industrial Development Organization, 2021).

Table 1.3 Estimated annual shipments of multipurpose industrial robots (number of units)

Country	2016	2017	2018	2019	2020*	2021*	2022*
America	41.295	46.118	44.300	44.300	49.616	55.570	62.238
United States	31.404	33.192	35.000	35.000	39.200	43.904	49.172
Canada	2.334	4.003	3.500	3.500	3.920	4.390	4.917
Mexico	5.933	6.334	4.500	4.500	5.040	5.645	6.322
Brazil	1.207	961	900	900	1.008	1.129	1.264
Rest of South America	394	300	400	400	448	502	562
America unespecified**	23	1.328					
Asia/Australasia	190.542	261.826	298.150	298.150	333.928	373.999	418.879
China	87.000	137.920	165.000	165.000	184.800	206.976	231.813
India	2.627	3.412	4.500	4.500	5.040	5.645	6.322
Japan	38.586	45.566	54.000	54.000	60.480	67.738	75.866
Republic of Corea	41.373	39.732	41.000	41.000	45.920	51.430	57.602
Taiwan, province of China	7.569	10.904	13.000	13.000	14.560	16.307	18.264
Thailand	2.646	3.386	4.000	4.000	4.480	5.018	5.620
Vietnam	1.618	8.252	2.500	2.500	2.800	3.136	3.512
other Asia/Australasia	9.123	12.654	14.150	14.150	15.848	17.750	19.880
Europe	56.078	66.259	70.950	70.950	79.464	89.000	99.680
Central/Eastern Europe	7.758	10.538	13.500	13.500	15.120	16.934	18.967
France	4.232	4.897	5.200	5.200	5.824	6.523	7.306
Germany	20.074	21.404	22.500	22.500	25.200	28.224	31.611
Italy	6.465	7.713	9.000	9.000	10.080	11.290	12.644
Spain	3.919	4.180	4.700	4.700	5.264	5.896	6.603
United Kingdom	1.787	2.334	2.400	2.400	2.688	3.011	3.372
Rest of Europe	11.706	12.133	12.850	12.850	14.392	16.119	18.053
Europe unespecified**	137	3.060	800	800	896	1.004	1.124
Africa	879	451	500	500	560	627	702
not specified by countries	5.553	6.681	7.100	7.100	7.952	8.906	9.975
TOTAL	**294.347**	**381.335**	**421.000**	**421.000**	**471.520**	**528.102**	**591.475**

* forecast

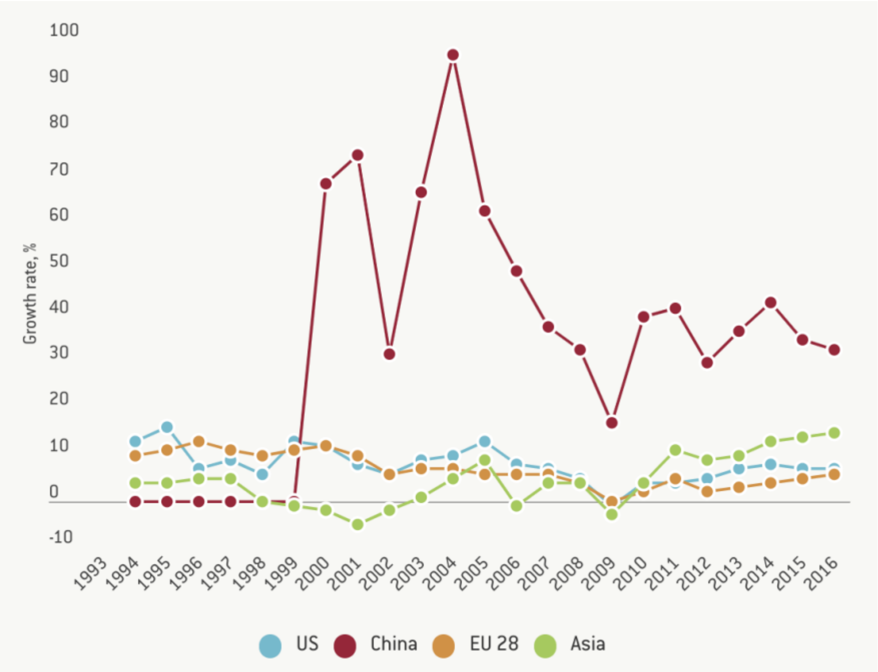
** reported and estimated sales which could not be specified by countries

Source: International Robot Federation, national associations (2018), own update in 2020.

In terms of monetary units, growth is expected from $37 billion in 2020 to $102 billion by 2025 (Paluch et al., 2022).

Despite the inexorable rise and random fluctuations between regions in industrial robot shipments, the race for technology is both competitive and global due to China's leadership.

Figure 1.3 Growth of operational stock of industrial robots

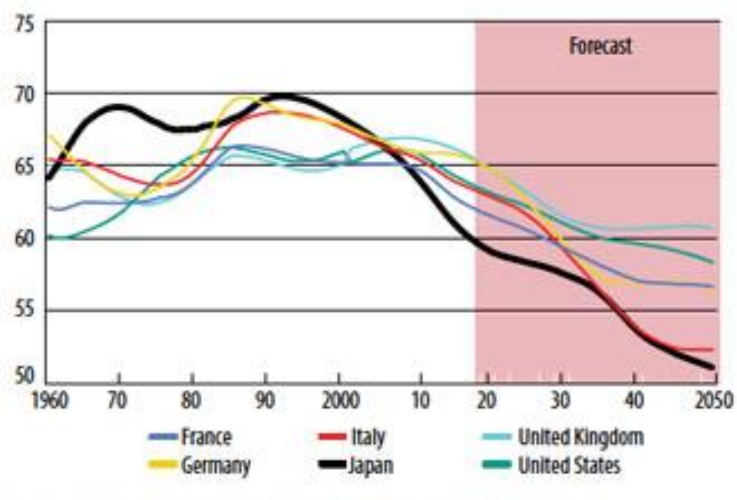


Source: International Robot Federation (2017).

New technologies not only provide connectivity opportunities for the entire population, but also impact almost every business activity. For example, they have changed consumption habits and the cost-competition model, caused technology prices (robots) to fall by increasing demand, and hand-in-hand with digital platforms, they have fostered the well-known "gig economy" (Lehrer et al., 2018). The gig economy has not only changed the volume and type of jobs available, but has also polarized job opportunities by encouraging inferior and extremely temporary jobs. This has led to a change in employment rules, as shown by the European Directive 2019/1152 on transparent and predictable employment conditions in the European Union, which introduced new minimum rights and new rules for informing workers about their working conditions. Considering the above mentioned elements, it is not surprising that many people would be afraid about losing their current jobs due to robotization. In fact, although robotization brings a lot of advantages for society (Weiss et al., 2011), one of the greatest challenges when it comes to introducing robots into the workplace is to convince team members that this fatalist theory is not properly founded. Business leaders and academics should therefore immediately try to tackle this concern by basing their arguments on data and analysis. This is especially true for organizations that are eager to compete in this new era. To address this objective, other aims of this dissertation are to understand what the main drivers, conceptions, perceptions, concerns, and areas of resistance are in this context, and to provide valuable inputs that reassure employees that, while their jobs may change or even disappear as they are today (Frey & Osborne, 2017; Vermeulen et al., 2018), this trade-off is not necessarily negative since new forms of employment and terms of employability are possible (Faber, 2020).

In fact, in most factories where robots have been introduced, management has not cut jobs, but has instead reassigned employees to other roles or departments that require greater added value through human intelligence and skills (United Nations, 2022). It could be even argued that automation is offsetting the decline in the human workforce in advanced economies (Figure 1.4).

Figure 1.4 Working-age population (% of total population).



Source: United Nations, World Population Prospects (2017 revision).

Moreover, if we review the recent evolution of industries, we find that automation and the use of robots have enabled certain types of manufacturing activities that several decades ago were sent to other countries or regions to be "onshored" (Faber, 2020), i.e. sent back to their countries of origin (CoO). One example is Adidas, which in 1990 decided to move its operations to China. Returning to Germany 25 years later, with the construction of an automated factory in which 160 employees merely supervise robots (The Economist, 2017). Of course, if organizations and society in general are unable to clarify this context, it will be difficult to generate the required sense of trust, security, commitment and engagement, especially from employees and consumers. Especially in case of some companies and industries, when global figures and literature contradict this tendency (Dachs et al., 2019). According to these authors, fewer than 4% of the corporations have back-shored operations to their country of origin (CoO). At this stage, however, the trend towards a positive correlation between the development towards Industry 4.0 and decisions for backshore operations is relevant.

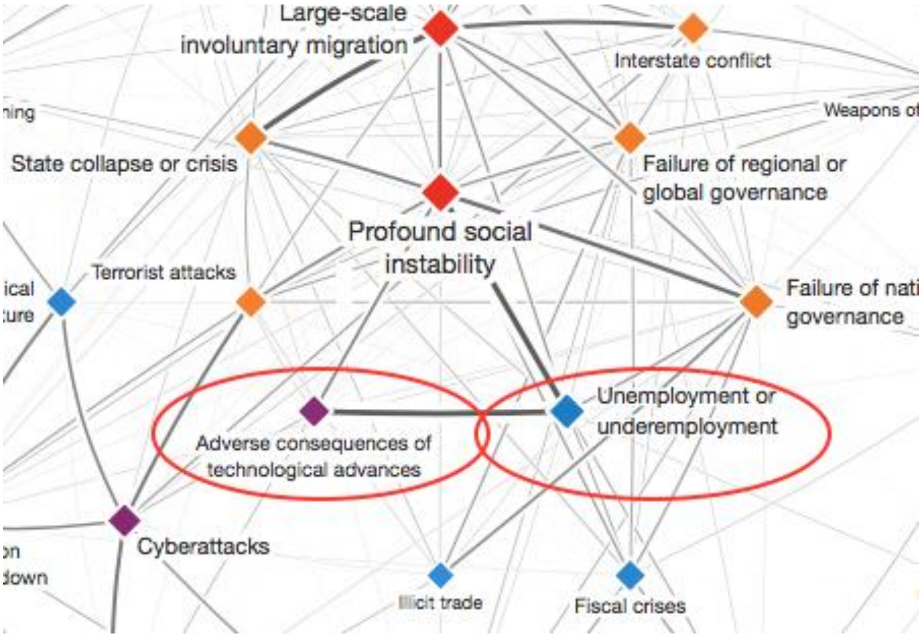
Clearly related to the above idea, it is worth remembering that the adoption of technologies has long had a positive impact on business performance in terms of productivity and lead time reduction, which has obviously led to higher profitability (Garsombke & Garsombke, 1989). These advantages are perceived very positively mainly by customers (Neugebauer et al., 2016), and consequently by shareholders since they contribute to higher profits. In addition, studies have shown that sustainability is directly linked to organizational and technological innovations that impact net and sales returns (Nidumolu et al., 2009).

The relevance of this research is further reinforced by the fact that twenty-five European countries have recognized that the socio-economic impacts of robotization must be "carefully managed". Having detected a gap in terms of required skills for this new scenario, in 2018 these countries signed a Declaration of Cooperation in Artificial Intelligence to define a European Approach to Artificial Intelligence and Robotics that addresses issues such education, training, development and changes in the labor market. The aim of the European Union is to make artificial intelligence (I5.0) both human-centric and trustworthy.

Today there is no doubt that robotization has had an impact on people, countries (Carbonero et al., 2020; Hollon & Rogol, 1985; Manyika et al., 2013; Muro et al., 2019), industries and companies (Olmstead & Rhode, 2001; Wang, W. & Siau, 2019). This has led to other initiatives from the European Union such as *Inclusive Robotics for a better Society* (INBOTS.eu), a platform that aims to promote a series of debates on the ethical, legal and socioeconomic barriers surrounding robotics, such as liability, risk management, insurance, intellectual and industrial property, interactive robotics in the labor market, social security law and, of course, the human acceptance of interactive robotics and potential corporate behaviors for promoting engagement with strategies for social responsibility. And at the global level, in its 2018 report the World Economic Forum[1] (WEF) conducted a diagnosis of global risks that placed the *adverse consequences of technological advance* at the center of the map (Figure 1.5) and linked them directly to unemployment or sub-employment.

[1] Swiss Think-Tank

Figure 1.5 Interconnections between global risks



Source: World Economic Forum (2018).

Logic supports the theory of fear about robotization, and interpreting this new global context is difficult. Although in 2018 the WEF puts new technologies at the center of global threats, this institution together with other experts and Key Opinion Leaders (KOLs), acknowledge that around 75 million jobs will disappear and 133 million new jobs will be simultaneously created, in areas such as customer service and related, generating more creative tasks and other employment modalities. Probably because of these reasons, five years later in 2023 the WEF map of risks is mainly concerned about a generic "erosion of social cohesion and social polarization".

From a more local perspective, the Hays[2] Labor Market Guide 2018 (Hays, 2018) asserts that in the Spanish labor market alone, almost 40% of startup companies have incorporated automated processes under different formulas. Apart from certain

[2] Hays is a Global Recruitment and Selection Consultancy Firm

percentages in specific sectors, innovation is no longer optional but essential for dealing with current operating business rules. Moreover, innovation is of course even more essential for companies in the startup sector because applied technology is their "leitmotif".

But surprisingly, the same report (Hays, 2018) indicates that for other types of companies this trend has been downwards compared to 2017. Moreover, despite the increase in news related to this phenomenon, in SMEs the replacement of employees by technology only applies to 24% of the organizations. Perhaps it is not a matter of the number or the percentage of companies that are automating their activity, but how deep the transformation is and which model is being adopted. This decrease may be the result of a standby approach by companies in relation to this kind of decision in anticipation of new technological contributions, regulations or simply a clarification of the overall context and competitors' strategies in this regard.

In any case, although automation and robotization in particular may be seen as threats due to the loss of jobs involved (Ford, 2015), certain key positive aspects can also be mentioned regarding the new business models and the improvements made (Smids et al., 2020). In terms of health and safety at work (Bicchi et al., 2008; Edmondson, 2004; Lee, J. et al., 2009), production costs have decreased, which may benefit consumers in terms of lower prices (Rust, R.T. et al., 2012), increasing the market demand and subsequently the employment. At the same time, however, this new technology (e.g. servers, the internet, processors) is not as environmentally friendly, as it requires a huge amount of energy to operate (Lin, P. et al., 2011).

Directly linked to robotization, another important aspect to analyze is related to the challenges that business leaders have in front of a technological decision (Ballestar et al., 2022). Sometimes they may feel unsecure, perhaps because of the degree of uncertainty that accompanies since the effort required to use a certain technology and the acceptance level of employees are largely unknown (Hwang, Y. et al., 2016). Moreover, the technology may evolve even before it is implemented, generating a logical frustration in employees during this transition (Lu et al., 2020; Paluch et al., 2022).

Having stressed the relevance of robotization and technology acceptance, there are implications as well on people management. According to the Gartner[3] *2023 HR Priorities Survey report*, the top five priorities for Human Resources leaders are:

Priority **1** (Leaders and Manager Effectiveness), depending on how the company is properly organized and how available resources (people and technology) to ensure an effective performance; priority **2** "(Organizational Design and Change Management) is related to the robotization process since it clearly involves a pre-definition of the expected organization, layout and performance as well as agility to change and acceptance from both employees and the overall organization; priority **3** (Employee Experience) makes it clear that acceptance in terms of expected performance, expected effort, perceived risks and facilitating conditions will determine employee experience; priority **4** (Recruiting) is strongly linked to employer branding and the reputational implications of robotization (as we will see in the next chapters); and priority **5** (Future of Work) encompasses the implications of robotics and the future of work within organizations and their impact on society in general.

1.3 Research objectives

[3] Gartner is one of the most relevant management and technology consultancy firms at global level.

Inasmuch as this study is conducted through a model of technology acceptance and the model reflects how users accept and use a certain technology, this thesis should focus on robots that, though they may lead to the elimination of jobs, should be understood not necessarily as a threat for incumbents, at least in the short term, but as a tool or support for doing the job – in some cases like a co-robot or colleague, i.e. as an element that could improve employee performance even though its implementation may result in job cuts. Otherwise, this research would not be about acceptance and use but acceptance due to imposition, since under normal circumstances no employee wants to lose their job. Based on the technology acceptance model, this dissertation attempts to answer the question "*How employees accept robots at work*" and to shed light on the following:

- Which factors may determine robot acceptance at work?
- Do employees recognize exposure to robotics as an employability advantage?
- Does robotization have a positive influence on the workplace?
- Is robotization perceived (by employees) as a tool for improving (their) performance?

As well as providing answers to these previous questions, this dissertation aims to:

- review the state of the art of intelligent automation and, more specifically, robotization within organizations by outlining the theoretical background for the research and evaluating the perception of different stakeholders, specially the employees.
- describe the methodological approaches based on the technology acceptance model that have been followed in conducting this research and consider the theoretical frameworks and additional aspects related to the types of interaction

with robots that help to interpret how employees perceive and prefer the presence of robots in the work environment.

- present empirical findings from the administered questionnaire; discuss the contributions in the literature on robotization and the acceptance of robotization by employees, proposing further guidance for practitioners and scholars.
- provide clarity on robotization and management as a guide for facilitating future research.

CHAPTER 2. THEORETICAL FRAMEWORK

2.1 Introduction to the theoretical framework

Since earlies 80s, there has been controversy about the impact that machines and information technologies could have on work and consequently on employees (Attewell & Rule, 1984), both from a positive perspective and from a much more pessimistic and devastating vision that in recent years has been strengthened. Starting from the initial automation, in a second stage we should add “digitalization stage” corresponding with the third industrial revolution (Rifkin, 2011). This step should be understood as a mere translation into bits of any element (Ortigoza-Limon, 2018) converting documents, music, images or social networks, among others, to a language compatible with computers to be subsequently managed or processed.

This digitalization is what has led us to "machine learning" or machine learning of computers, serving as the base for development the latest generation of robots and technologies. Finally, when we refer to **robotization** or robotic automation we are referring to industrial or business automation processes, although such robots may adopt very diverse natures and appearances, capable or intended to replace functions that have traditionally been performed by people (Frey & Osborne, 2017; Muro et al., 2019). Although having executed an uncountable variety of robotizations during the last decades, it is currently when they are proliferating the most (Lee, J. et al., 2014), assuming a relevant place in the so-called fourth industrial revolution (Shrouf et al., 2014).

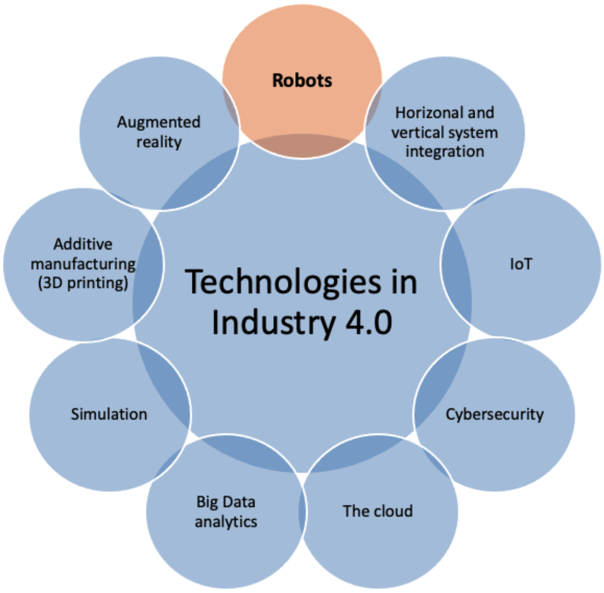
Same as any other technology, robotization and intelligent automation (AI, IA, RPA), may represent a new source of competitive advantage (Porter, 1985; Powell & Dent-Micallef, 1997; Taylor & Raden, 2007; Stajkovic & Sergent, 2019) offering the possibility of radically altering many industries (Wang, W. & Siau, 2019). In addition, this transformation has brought a new way to compete more efficiently in markets (Autor

& Salomons, 2018; Doraszelski & Jaumandreu, 2018; Aghion et al., 2019; Ballestar et al., 2021) with new tools like AI (Artificial Intelligence), IA (Intelligence Augmentation) and RPA (Ng et al., 2021).

With the aim of framing the definition of this research, one of the purposes would be to generate knowledge and key information on how to prepare organizations for this new reality that is rapidly approaching and that, at it will stay. Over the last few years, various frameworks have been developed addressing a new context of industry 4.0 and 5.0, and how to understand robotization as a general process, and more specifically robotization at work (Ghislieri et al., 2018).

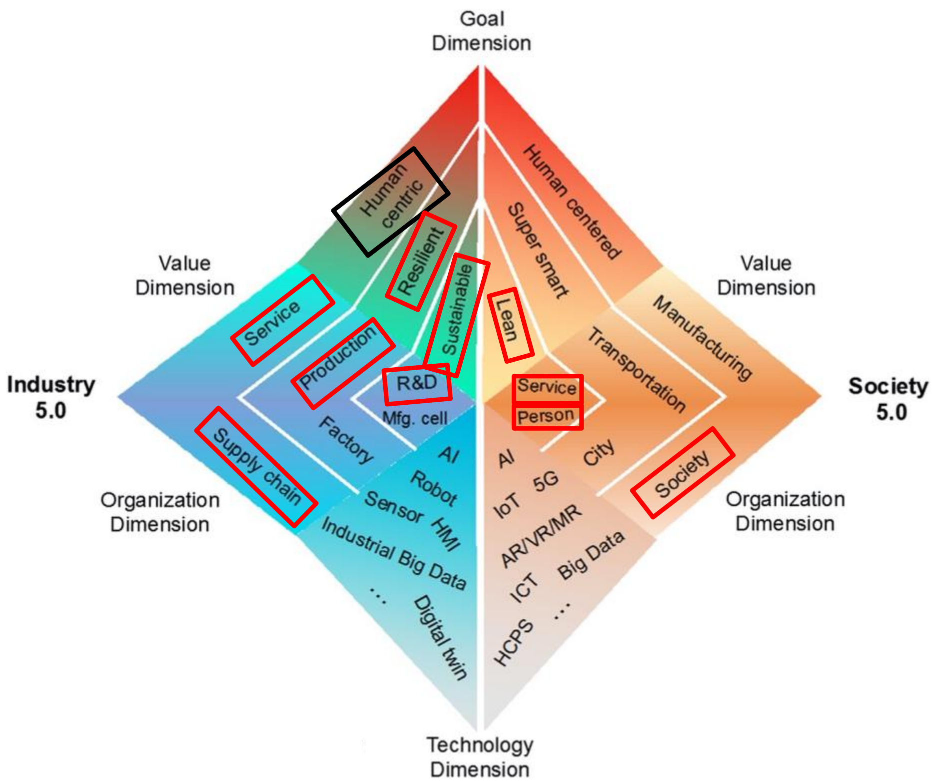
While Industry 4.0 (Figure 2.1), can be described as an innovative digitalization in every industry (Lasi et al., 2014; Molitor, 2020; Parvez et al., 2022), the new concept of Industry 5.0 (Figure 2.2) brings much more interest for this dissertation, as introduces a new human-centric and sustainable approach towards the human-machine interaction (European Economic and Social Committee, 2018; Breque et al., 2021), to address needs from employees, organizations and to solve problems in current society. Understanding society, as the place where everyone can enjoy, thanks to information and communication technology, of a high-quality and comfortable life through the fusion of cyber and physical space (Huang, S. et al, 2022). Nevertheless, we refer very broadly to these new "industries" despite these concepts refers to an overall interconnected industry and not necessarily just to robotization (Bahrin et al., 2016), what represents just one of its drivers.

Figure 2.1 Drivers related to Industry 4.0



Source: Own development based on Bahrin et al. (2016)

Figure 2.2 Industry 5.0, Society 5.0 and people management



Source: Own development based on Huang et al. (2022).

This new model of industry 5.0 promotes actions on sustainability, talent management and organizational diversity. In particular, pays attention to rational dimensions that are relevant for company' stakeholders (Barnett & Salomon, 2006; Chun, R., 2005): promoting a human-centric organization is considering the workplace (He et al., 2019; Smids et al., 2020); also, the value dimension of services and production (Prabhu, 2012; Sa & Hambrick, 1989); and R&D is another key dimension merged with innovation (Huarng et al., 2018; Van Reenen, 2020; Wang et al., 2023). In addition, to develop a resilient organization, it requires a good leadership (Anderson & Ackerman-Anderson, 2010; Finkelstein & Hambrick, 1996). An efficient supply chain dimension together with lean practices, should bring a better performance (Wall, T.D. et al., 1990) and of course, the overall orientation towards society is linked to citizenship and governance (Dunleavy et al., 2006; Rangel-Pérez et al., 2023).

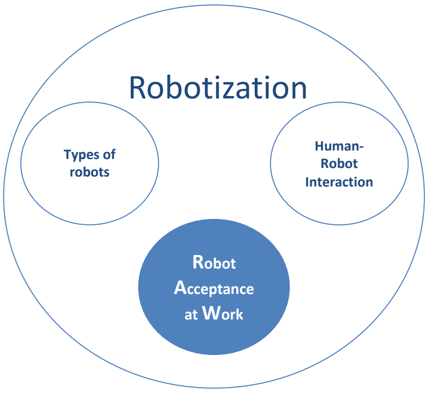
Before formulating the complete model for this research, in Figure 2.3 it is shown a summarized version of the framework for current research, showing the relevance of robotization through three different aspects:

The **types of robots** and how important is to understand that there are different ways to analyze a robot.

Secondly the relevance of the **Human-Robot Interaction** (HRI) under its very different ways and implications.

And the **acceptance of robots at work** which will be analyzed under the Cognitive-Affective-Normative (CAN) model.

Figure 2.3 General scheme of the research



Source: Own development

It is all about addressing robotization in organizations, the acceptance of such transformation by employees to finally generating a framework to understand better how to design robotization initiatives, considering that the success in an automation or robotization process may depend on the role of human resources management and the effective involvement of employees (Parvez et al., 2022), as well as the response from stakeholders (Zhong et al., 2022). In short, the assessment of how the integration of machines and people can be carried out effectively (human-robot interaction and collaboration), considering the perception of employees.

Current and future **employees**, main actors in the chosen theoretical model that will allow to analyze their **technological acceptance**. The methodology, as developed in the corresponding chapter, will be the Cognitive-Affective-Normative model (Pelegrín-Borondo et al, 2017). Serving as a fundamental ground for this dissertation (Davis et al., 1989; Huang & Rust, 2017; Molino et al., 2021).

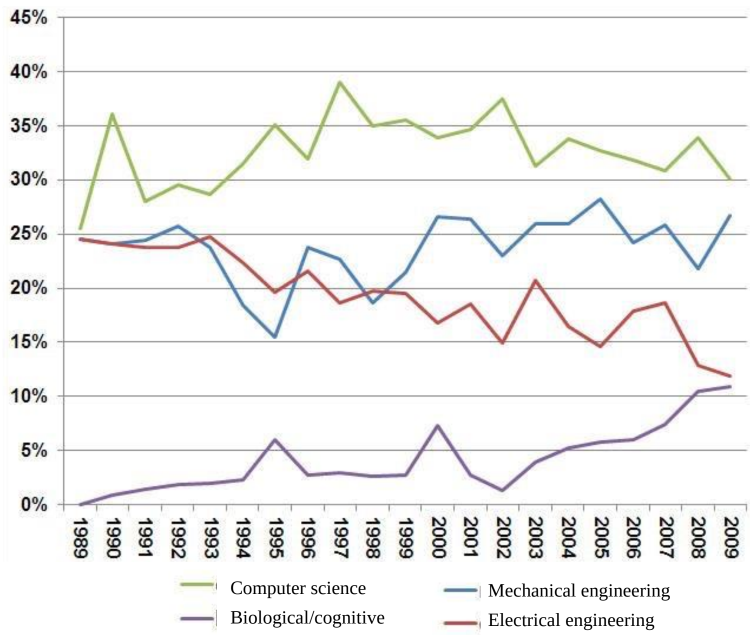
2.2 Robotics

It is widely considered as an interdisciplinary field of study (Birk, 2011), and following a holistic definition, we could describe it as the scientific and engineering discipline concerned with the creation, composition, structure, evaluation and properties of embodied artificial capabilities (Redfield, 2019).

This would be fully accurate, if we would refer just to robots as traditionally (physical and embodied) known. But today, this scientific conceptualization of robotics leaves some grey areas related to non-physical automatisms which are usually considered as robots because in the end, perform tasks in an autonomous way, that traditionally were performed by humans (Artificial Intelligence).

To understand better the complexity and its interconnexion with others see below in Figure 2.4, how biology and cognitive biology has emerged from 2002.

Figure 2.4 Authors' affiliation in robotics discipline



Source: Birk (2011)

This contextualization helps to understand the extension of current sub-chapter dedicated to robotics. Which will introduce aspects as relevant for this dissertation, as the concept and types of robots; the process of robotization in general terms, showing as well positive, negative and controversial implications related to robotization. Before concluding robotics, it will be reviewed the concept of Human-Robot Interaction (HRI), which is completely relevant for the main body of the dissertation. To conclude, some figures and forecast will be shared to provide additional context.

2.2.1 Concept of robot

According to the ontological analysis performed by Prestes et al. (2013), a **robot** would be a *device with mechanical parts, but it would also be an agent that interacts with the environment, which can compose systems with its environment*. The Oxford English Dictionary defines **automation** as the *use of electronic or mechanical devices to replace human work*. Then, it seems that automation and robotization are intimately related.

The word "robot" originated in 1920 from the Czech science-fiction play "*Rossumovi Univerzální Roboti*" (R.U.R.), written by Karel Čapek. In this play, the word "*robota*" was introduced, which means servitude, slave, or forced labor. Interestingly, the credit for the term "*robot*" should be attributed to Karel's brother Josef, as he had already used the term "automat" in 1917 in his work "*Opilec*."

R.U.R's robots were born in order to lighten workload and help employees. The plot begins in a factory which produces artificial humans (*roboti*). These non-natural humans were created from synthetic organic materials, being able to think by themselves, and physically similar to a human. The play became a drama, because despite those robots felt initially happy working for humans, they revolted and decided to terminate humans.

Figure 2.5 Covers of the play R.U.R

Source: Original cover design by Josef Capek, Prague (1920) | Marionette Theatre, NY (1939) | Remo Bufano, NY (1939)

Since the last six decades until now, in the manufacturing industry, the reference to robot has been very evident (Figure 2.6). Despite there are multiple types of robots, in the industrial environment, most of them are recognized by its articulated appearance

Figure 2.6 Industrial robot

Source: Universal Robots[4]

[4] Universal Robots in an US robots manufacturer

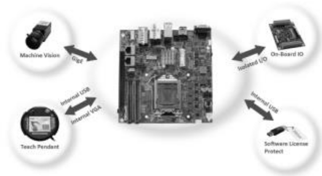
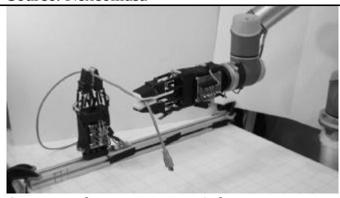
According to the definition of the ISO 8373:2012[5], it would be *an actuated mechanism programmable in two or more axes with a degree of autonomy, moving within its environment, to perform intended tasks*. The International Federation of Robotics (IFR) details a bit more the definition of industrial robot, incorporating some interesting elements: *Being of a "reprogrammable" nature, it must be an artifact designed so that both the initially programmed movements and their auxiliary functions can be modified without having to physically alter the device*. With multitasking capability, it must be physically adaptable to carry out new functionalities. In this sense, alteration or physical adaptation, refers to changes in their mechanical system, and not to their storage of information or memory. Under this prism, gadgets such as a coffee vending machine or the elevator should not be considered industrial robots.

However, to better understand the concept of robot and robotization, it is recommendable to become familiar with its specific terminology. For that purpose and based on the latest ISO's development, the Table 2.1 contains a summary of the most relevant concepts related to robot and robotic devices, with some additional context.

Table 2.1 General terms related to robots and robotics devices

Autonomy	To perform intended tasks based on current state and sensing, without human intervention.
Physical alteration	Alteration of the mechanical system initially defined. It does not include changes in media storage, ROMs, etc.
Reprogrammable	Designed so that the programmed motions or auxiliary functions can be changed **without** physical alteration.
Multipurpose	Capable of being adapted to a different application **with** physical alteration.
Operator	Person designated to start, monitor, and stop the intended operation of a robot or robot system. In the questionnaire it is formulated one specific question about his type of interaction (operator, programmer…).
Programmer	Person designated to prepare the task program of the robot.
Recipient	Beneficiary or person who interacts with a service robot to receive the benefit of its service. It should not be the operator. For instance, a patient receiving care from a medical robot.
Robot cooperation	Information and action exchanges between multiple robots to ensure that their motions work effectively together to accomplish the task.

[5] The ISO (International Organization for Standardization) 8373:2012 defines terms used in relation with robots and robotic devices operating in both industrial and non-industrial environments.

Manipulator	Machine in which the mechanism usually consists of a series of segments, jointed or sliding relative to one another, for the purpose of grasping and/or moving objects (pieces or tools) usually in several degrees of freedom**.** A manipulator can be controlled by an operator, a programmable electronic controller, or any logic system (for example camera device, wired).	 Source: Thingbits Electronics
Control systems	Set of logic control and power functions which allows monitoring and control the mechanical structure of the robot and communication with the environment (equipment and users).	 Source: Nexcomusa
Robot	Mechanism programmable in **two or more axes** with a degree of autonomy, moving within its environment, to perform intended tasks. It includes a control system and an interface to the control system. Depending on its intended application it can be classified as industrial or service robot.	 Source: Robots-RT en Español
Robotic device	Mechanism fulfilling the characteristics of an industrial robot or a service robot but lacking either the number of programmable axes or the degree of autonomy. Some examples would be a teleoperated device or a two-axis industrial manipulator**.**	 Source: Chengdu Fuyu Technology Co., Ltd
Industrial robot	Automatically controlled, reprogrammable, multipurpose, manipulator and programmable in **three or more axes**. Those axes can be either fixed or mobile for use in industrial automation applications.	
Service robot	Robot that performs useful tasks for humans or equipment, excluding industrial automation applications. Their classification depends on the expected utility: while articulated robot used for production lines are industrial, similar articulated robots used for serving food are considered as service robots.	 Source: Beijing Yunji Tehnology
Personal service robot	Used for a non-commercial task. Typical applications can be domestic servant robot, automated wheelchair or personal mobility assist robot.	
Professional service robot	Used for commercial tasks, usually operated by a properly trained operator. Some examples could be cleaning robot for public places, delivery robot in offices or hospitals, fire-fighting robot, rehabilitation robot or surgery robot in hospitals.	
Intelligent robot	Robot capable of performing tasks by sensing its environment and/or interacting with external sources and adapting its behavior. For instance, industrial robots with vision sensor to pick and place an object; collision avoidance; legged robot walking over uneven terrain.	
Integration (swarm robotics)	Multi-agent systems. Combining a robot with other equipment or another machine (including additional robots) to form a machine system capable of performing useful work such as the production of parts. This concept (integration) has been traditionally endorsed in industrial environments. Nowadays there are complex systems (swarm robotics) for security, military and natural disasters (Arnold et al., 2019).	

Source: Own development based on ISO 8373:2012 and authors.

However, in the administrative and managerial context, robot is less tangible (RPA). It can be a device, software or a mere functionality that accomplishes the functions previously performed by a person (Parasuraman & Sheridan, 2000; Madakam et al., 2019).

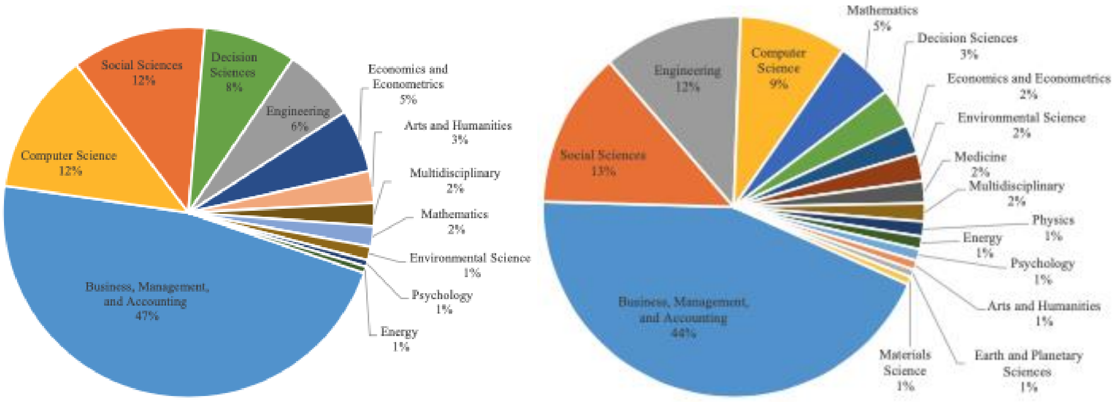
In this sense, functions such as voice recognition and response, as well as the query and response system of a "chatbot", would be examples of robots that do not require a physical device. In general terms, when we refer to **robotic automation** or **Robotic Automation Process (RPA)**, we usually refer to that technology in the service sector (back office and front office activities in any industry), which is capable or intends to replace functions that have traditionally been performed by people (Anagnoste, 2017); while the concept of **robot** usually refers to the adoption of automated processes in production areas.

At present, **artificial intelligence** is one of the most decisive elements for the development of robotics in non-industrial environments (Roser, 2022). Its development began more than 70 years ago since the Second World War, in which the mathematician Alan Turing and the neurologist Grey Walter set out to work together for its development, justifying that computers would think as we humans do or at least, "*deceiving a human into believing that the machine was human*" (Turing, 1950).

Artificial Intelligence together with RPA drive organizations, businesses, and their related technology transformation (Madakam et al., 2019). Improving human intelligence, tries to facilitate the decision-making process within the organizations, and being strongly linked to administrative and managerial functions (Ng, K. K. H., Chen, Lee, Jiao, & Yang, 2021).

In fact, based on *Scopus*' data and the *Technological Forecasting & Social Change Journal* (Figure 2.7), most of the knowledge and research about Artificial Intelligence, flows **to/from** the discipline of "**Business, Management and Accounting**". This discipline represents a 47% and 44% respectively, while "Computer Science" and "Social Science" represent 12% each of them in both senses (Dwivedi et al., 2023).

Figure 2.7 Knowledge (in/outflows) related to Artificial Intelligence

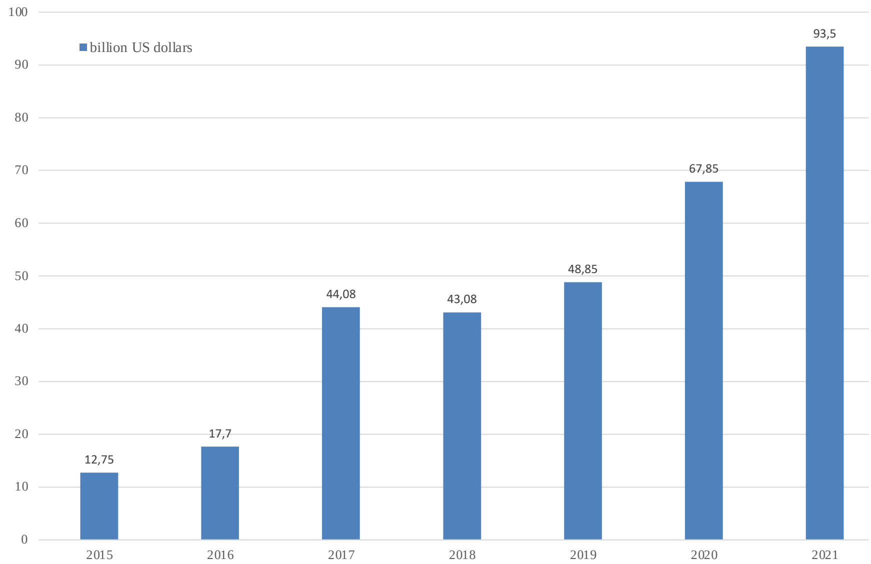


Knowledge inflow to the Journal AI Research **Knowledge outflows from the Journal AI Research**

Source: Dwivedi et al. (2023); TF&SC Journal and Scopus

Like almost all great challenges, at earlier stages required progressive monetary investments with certain/minor progress. But considering its high potential, global investment in AI has step-up in the last decades, when it has been multiplied by seven (Statista, 2023), moving from 12.75 B$ in 2015, up to 93.5 B$ in 2021.

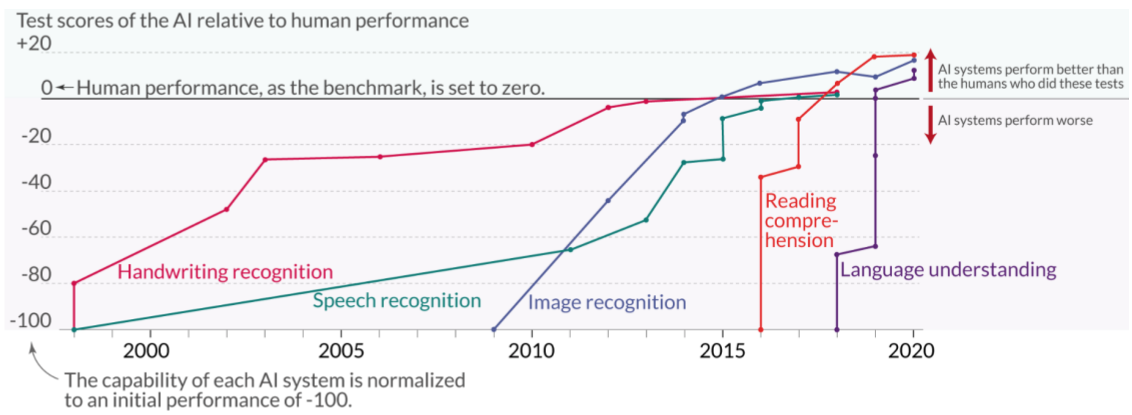
Figure 2.8 Global corporate investment (AI)



Source: Statista (2023)

This investment together with extraordinary efforts from research, has generated an unpredictable technological progress, especially in reading comprehension, image recognition and language understanding, if compared to human standards. These capabilities are directly impacting into industries, business models and general society (Chauhan et al., 2022; Dwivedi et al., 2023).

Figure 2.9 Language and image recognition capabilities of AI systems



Source: Kiela et al. (2021) and Roser (2022).

In fact, the vast majority of robotic functionalities in the field of services, administration or management are supported by algorithms. Some examples are monitoring an event, virtual archiving, reading data, creating documents, making decisions based on predefined set of conditions or sending confirmations (Willcocks et al., 2015). But this should not be understood like “*developing an algorithm is the same as a robotization process*”. Algorithms can be translated as well, into specific actions that have never been performed by humans. In fact, the most important expectation, is about what it will be done in the future, that has not been done yet.

2.2.2 Classification of robots

Robots can be differentiated according to different aspects such as anthropomorphism, the orientation they have towards the task or their own representation (Wirtz et al., 2018; Paluch et al., 2022).

Table 2.2 Classification of robots

In terms of	Comments	Authors
Autonomy	-From reduced to full autonomy.	Parasuraman & Sheridan (2000) Ng et al. (2021)
	-Required attention. -Task effectiveness. -Neglect tolerance. -Interaction effort. -Fan-out	Olsen & Goodrich (2003) Huang et al. (2003)
Physical/ non-physical	-Morphology. -Motor system. -Location. -Control architecture. -Sensory systems. -Human similarity. -Avoiding human appearance.	Siciliano et al. (2008) Fong et al. (2003) Ng et al. 2021
Human-Robot Interaction	-Autonomy. -Levels of interaction. -Application.	Benbasat & Barki (2007) Venkatesh et al. (2007) Cesta et al. (2016) Sheridan (2016) El Zaatari et al. (2019) Paliga & Pollak (2021) Segura et al. (2021)
	-Work roles.	Bratman (1992) Scholtz (2003) Segura et al. (2021)
	-Interface communication. -Programming interaction. -Intuitiveness.	Villani et al. (2018) Segura et al. (2021)
	-Safety control	International Organization for Standardization, ISO 15066 (2016)

Source: Own development.

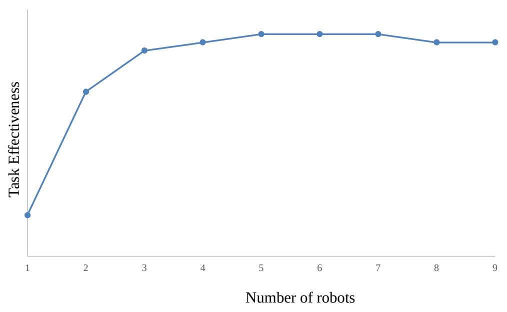
The first distinction is that robotization can represent the replacement of all, or part of the tasks performed by humans. This approach is based on the fact that robotization does not represent necessarily an absolute term (everything or nothing), but it can vary depending on device's **autonomy**, fluctuating from a reduced to a full automation.

In that sense, and according to Parasuraman and Sheridan (2000), it should be distinguished from a very low level of automation (when the device does not offer any assistance to the employee -just physically-), being the employee who has to make all the decisions and to act. This would correspond with electronic or mechanical devices that the employee has to activate, as for instance, the access barrier of a parking area, where it depends completely on the activation of the guard (Sheridan, 1992).

A second step in terms of autonomy, it would represent those systems in which the human has a time of response to veto the robot's action or to define another procedure (Parasuraman & Sheridan, 2000). In these cases, the machine executes if human approves. It would be up to this level, when human has control over robot's decisions, and even over the final outcome. A third level with a bit more of autonomy would correspond to those systems in which the machine only informs or asks to the human, followed by a robotization model in which the machine only informs the human in case of being asked, until reaching the highest level of automation in which the device decides everything, autonomously and ignoring the human factor (Parasuraman & Sheridan, 2000).

Other authors have developed similar distinctions in terms of autonomy, but assessed in terms of **required attention, task effectiveness, neglect tolerance, interaction effort and fan-out** (Olsen & Goodrich, 2003; Huang et al., 2003). This approach is mostly relevant for unmanned robots (devices without presence of humans in control) mainly used for military purposes and rescue missions (Huang et al., 2003). In relation to this classification, there is a great disparity of technologies and devices. In this classification is more relevant the process' definition, than the technology itself. The capability of the robot determines its autonomy; in the sense that requires less interaction (attention), the robot is highly effective on its assigned task without human supervision (task effectiveness), the robot is able to perform for a longer period since last time supervised or neglect time (Olsen & Goodrich, 2003). And last but not least, Figure 2.10 refers to fan-out (estimation of the number of robots that a human can operate at once). Above a certain number of robots operated by one human, the task effectiveness stays constant, then is always more efficient having fewer robots but with higher autonomy (Olsen & Goodrich, 2003).

Figure 2.10 Fan-out performance



Source: Olsen & Goodrich (2003).

Trying to classify robots, it is easy to classify the type of robot based on their functionalities (aerospace, underwater, consumer interaction, disaster response, education, entertainment, medical, exoskeletons, industrial, security, military, self-driving cars...). But for current research, this is not applicable. Their functionalities will be addressed under other chapters to analyze other aspects as social-impact, challenges, etc. But fur current research is more interesting to distinguish between characteristics.

Physical robot-automation

There are multiple aspects that should be considered in order to design a physical robo**t** (Siciliano et al, 2008): morphology, motor system, location, control architecture, sensory apparatus, etc. In terms of the morphology presented by Fong et al. (2003), we can point out robots that have been intentionally developed avoiding the human appearance, to be perceived as mere tools and not as "co-workers". In that group, just mention that Walmart incorporated some robots in 2017 (Schwab, 2019), initially to support the control of stocks and inventory. But three years later, Walmart decided to terminate the project, trying to explore different technologies. Now, they are exploring other ways to robotize their operations, like automating a task which was historically assigned to humans: to manage suppliers' negotiations through artificial intelligence (Van Hoek et al., 2022). This is an automation of tasks that reduce the physical interaction to zero, it represents an improvement in terms of efficiency for the company, and maybe as well for the contractor, without any commercial risk because the client is not aware (Ng, K. K. H. et al., 2021).

But some other companies in the same sector, but with a different "client segment", have decided to join robots in their stores to facilitate interaction with customers, providing details about products or store lay-out. In Europe there are some examples like Carrefour with "Pepper" and Sanchez Romero with "Romerito".

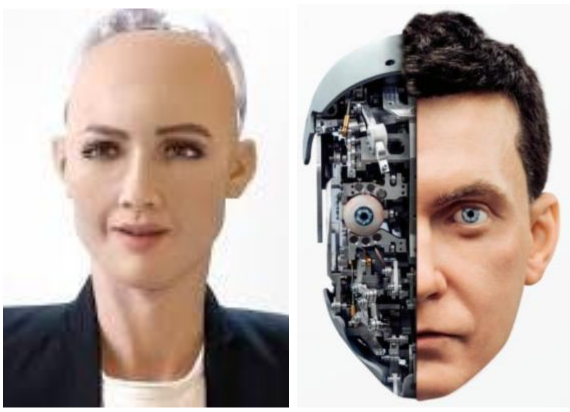
Framing these elements into the object of this dissertation, it should not be assumed that all the employees are going to be replaced by robots in these stores (Acemoglu & Restrepo, 2019), but companies try to develop a different customer and user experience (Vaidya et al., 2018), turning stores into places to enjoy unique experiences, accompanied by expert sellers who guide in a precise and personalized way according to their needs. In particular, if we segment the market, those lower-budget stores can be more robotized if translated into price reduction (Porter & Heppelmann, 2016).

On the other hand, in premium stores, customers highly appreciate and expect personalized human interactions. However, in the areas of warehousing, distribution, and inventory management, technology has the potential to easily replace employees. The crucial aspect lies in the sales and customer care roles, where differentiation can be achieved. These professionals should strive to make a significant impact by delivering exceptional performance that surpasses customer expectations and fosters a strong connection with them (Pine & Gilmore, 1999). By going above and beyond, they can provide a level of service that goes beyond what a robot can offer. This emphasis on exceptional customer experience can significantly enhance the company's reputation and turn these employees into genuine brand ambassadors.

Moving forward in the customer and user experience, robots like Sophia by Hanson Robotics[6] (Figure 2.11), try to simulate at maximum human traits, communication style and appearance. Its human projection goes even farer, with social media accounts in Facebook, Twitter, YouTube or Instagram. All of them, managed thanks to the dialogue system based on its (her) artificial intelligence.

But the latest advance on this field has been Robo-C2 from Promobot[7], which has incredibly improved its (his) physical appearance (Figure 2.11), functionality and human-interaction.

Figure 2.11 Humanoids robots (Sophia and Robo-C2)



Source: Hanson Robotics, HK (2015) | Promobot, US (2023)

In this sense, latest advances in robotics based on bioengineering, offer great opportunities for humanoids. One of the latest developments, from the Institute of Bioengineering of Catalonia (IBEC), consists of the development of synthetic tissues

[6] Hanson Robotics is a Hong Kong based company, specialized in humanoids.

[7] Promobot is a US robot manufacturer.

thanks to 3D printing. Although its direct implication will be with injuries or other pathologies, it will bring opportunities in the development of humanoids, offering appearance, movement and touch like human.

In the same direction, the robot H-1 is equipped with more than 13000 sensors simulating an artificial skin, what represents a leap in terms of sensitivity and affection from a machine.

Figure 2.12 H-1 humanoid with cells and sensors

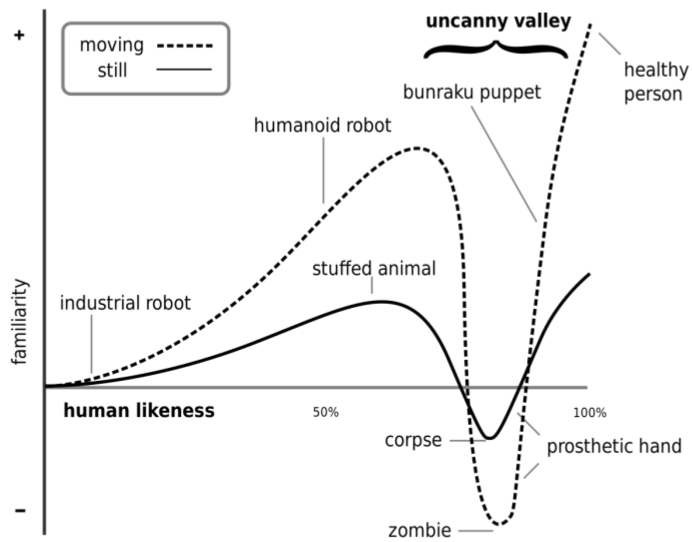
Source: Astrid Eckert. Technical University of Munich. Department of Electrical and Computer Engineering (2018).

It is expected that an android's embrace could generate similar stimuli than humans (Fong et al., 2003). These types of robots are initially conceived and oriented to tasks oriented to care and interact with people (Cheng et al., 2019; Wu, Y. et al., 2014), where predictably they will have a prominent role, more even considering the aging of the population in developed countries (WHO, 2022).

Nevertheless, referring to this physical appearance (morphology), it is important to make sure that the robot does not create false expectations. Related to that, it is important (to have additional references on this regard) to bring into attention Mori's theory "uncanny valley" (Fong et al., 2003). Despite after the time (since 1970) and taking into considerations all the technological advantages since then, his theory has not been fully validated (Brenton et al., 2005).

The Uncanny Valley theory, often referred to as the incomprehensible valley, is based on a notion developed more than 50 years ago by Masahiro Mori, a Japanese researcher on how people react emotionally to non-human beings. This author wrote "The Uncanny Valley" (in Japanese: 不気味の谷 bukimi no tani) in 1970. His idea examines the opposition that humans may exhibit when robots resemble people too closely, both in terms of their look, manner of moving or gesturing.

Figure 2.13 Theory of the Uncanny Valley



Source: Mashiro Mori (1970).

To conclude with the physical analysis of robots, as we already know, industrial robots are functional, and their design is more oriented to effectiveness and safety, than showing specific appearances.

Non-physical robot-automation

At this point, let us back on some concepts like Artificial Intelligence, which encompasses a broad range of techniques as for instance, machine learning (Ng, K. K. H. et al., 2021). It is a part of computer science that is focus on generating outcomes like humans but performing in a more efficient and consistent manner (Huang & Rust, 2018). It can be designed for different tasks like knowledge, reasoning, planning, problem solving and speech recognition (IBM Cloud Education, 2023).

Intelligence Augmentation: a different conceptualization of the previous concept, it is focused on enhancing instead of replacing human intelligence (Huang & Rust, 2018). It offers safer tools for image processing (Esteva et al., 2017), knowledge bases (Davenport & Kirby, 2015), electronic discovery and natural language, among others (Jarrahi, 2018).

Robotic Process Automation is currently defined as an automation technology which represents the base to accelerate rule-based decision making. The RPA is supported by robots or software agents, requiring a minimum human interaction or supervision (Ng et al., 2021). Functions such as voice recognition and response, as well as the query and response system of a "chatbot", would be examples of robots that do not require a physical device.

Research about how robots and human should interact and work sharing a common space has increased significantly (Paliga & Pollak, 2021). Based on its relevance, It has been considered HRI as one of the classification criteria, to be explained in the next sub-point.

2.2.2.1 Human-Robot Interaction

It is defined by ISO as "*Information and action exchanges between human and robot to perform a task by means of a user interface, as for instance, when there are some exchanges through vocal, visual or tactile*".

Since the emergence of phenomena such as digitalization and robotization, the literature related to the implementation of new technologies and automation in the work environment has increased significantly (Molet et al., 1989; Nemati et al., 2002), also trying to address topics such as human-robot interaction, that beyond fluctuations, has brought an increased attention for the last three decades (Table 2.3). HRI and its technological acceptance implications have been established as one of the main lines of research in the field of management and information systems (Benbasat & Barki, 2007; Venkatesh et al. 2007).

Table 2.3 Articles about HRI and Technology Acceptance

	Human Robot Interaction		Technology Acceptance	
Year	# articles	% increase vs previous	# articles	% increase vs previous
2022	1182	31%	2987	2%
2021	901	-7%	2927	10%
2020	972	409%	2662	239%
2010	191	582%	785	388%
2000	28	1300%	161	216%
1990	2	100%	51	410%
1980	1		10	

Source: Own research based on WoS (refined by areas of Business Economics, Psychology and Social Sciences).

Human-Robot Interaction evolves as much fast as robots do, having evolved from servomechanisms to artificial intelligence without human supervision.

HRI has been neglected by researchers if we compare to human-"automation" or human-"computer" interactions (Sheridan, 2016). There are several concepts that despite are different, are closely related, like automation, digitalization and robotization. It seems that robotization generates a certain neglection to be used in general terms, maybe because of the connotations that may represent from a social or employee perspective (in terms of job losses). In fact, even the companies are reluctant to use such "robotization" term, opting to choose terms such as digitalization or automation (Montero-Vilela et al., 2019). The annual ESG reports from the 35 biggest Spanish companies (IBEX 35[8]), have just referred 5% of the times to the word "robotization" instead of the 38% referring to "automation" or even the 58% corresponding to "digitalization" (Table 2.4).

Table 2.4 Mention of automation, digitalization and robotization by IBEX 35

		% mentions by industry		
INDUSTRIES	**# mentions**	**Automation**	**Digitalization**	**Robotization**
Energy	85	20%	76%	4%
Bank and insurance	65	34%	66%	
Information Technology	62	39%	58%	3%
Transportation	42	71%	24%	5%
Materials, Manuf. & Construction	40	43%	40%	18%
Leisure, tourism and hospitality	13	15%	85%	
Textile	12	67%	17%	17%
Media	11	36%	64%	
Real state	6	17%	83%	
Food and beverages	3	100%		
Trade	2		100%	
Pharmaceuticals	1	100%		
Total	**342**	**38%**	**58%**	**5%**

Source: Montero-Vilela et al. (2019) based on companies' ESG annual reports.

This difference in emphasis can be attributed to variations in the level of technological adoption across different industries (Tidd & Thuriaux-Alemán, 2016). While some industries may prioritize digitalization, not all sectors heavily invest in full-scale robotization. However, it is important to note that the categories of materials, manufacturing, construction, and energy collectively account for a significant 40% of all companies and ESG reports at IBEX35 stock market. Given this substantial representation, it is apparent that the assumption of limited grounding for the

[8] IBEX 35 is the benchmark stock market index of the Spanish stock exchange, which includes the 35 most traded companies in the four Spanish stock exchanges.

aforementioned industries is insufficient. These sectors, too, are witnessing technological advancements and exploring automation to varying degrees, making it crucial to consider their evolving landscape. Different technological approaches, that generate different HRI.

Human-Robot Interaction can be analyzed from multiple perspectives. According to Sheridan's classification (2016), first distinction, could be depending on the **level of robot autonomy and its application**:

(1) **Robots performing routine tasks**(manufacturing assembly lines, telerobots[9], etc. Communicating to human operators who are responsible to adjust or provide instructions depending on requirements.

(2) **Robots that assume nonroutine and risky tasks**, remotely controlled and that usually are assigned to tasks in hazardous or hardly accessible places. If they are more autonomous, are named "teleoperators" just informing to humans. In case do not perform the overall task, should be named "telerobot".

(3) **Automated vehicles**. Under this modality, the human has a passive role into the vehicle as passenger, or alternatively as bystander in the workplace.

(4) **Human-robot with social interaction**: those which provide support on entertainment, teaching and personal assistance or care.

Depending on the **specific applied technology**:

We can start with the most recent and disruptive robotization model: **data analytics and artificial intelligence**, understood as the ability of computers and other machines to work intelligently without human intervention (Davenport & Ronanki,

[9] Those devices are semi-autonomous from a distance mainly through wireless connectivity or tethered connections.

2018). In this area we find "machine learning" and "deep learning". Considering that according to IBM, already 35% of the companies are using AI and 42% are exploring its implementation, relying on **algorithms** in terms of robots, which assist them in a wide range of decision-making. We should know that without them had not been possible the new logistic approaches (Sarkis, 2012; Viale & Zouari, 2020), current air traffic planning and the urban mobility (Nikitas et al., 2020) or fraud risk detection as states today (Mhlanga, 2020). And of course, new functionalities like image recognition, bring multiple possibilities in terms of services, products and security (Esteva et al., 2017).

Under this somewhat intangible prism of robotic activity, and not being able to assimilate it to a certain physical form, we also find other robotic manifestations of artificial intelligence such as **bots (robot software)**, which turn out to be an interface that provides a service to the user, performing tasks of a repetitive nature through the support of internet (Lebeuf et al., 2019). In this case, the nature of robot is easily recognized since the performance of these specific tasks by an employee would be in many cases possible. But materially impossible in an aggregated manner, because of their repetitive nature, that it could even represent a psychosocial risk for the employee. Some examples of bots could be the search engines (Google, Yahoo, etc.) that in tenths of a second provide information that would be simply impossible for a human. In this sense, according to Google reports, they perform 150,000,000 searches per hour (on average), with more than 135,000 employees worldwide. Even in the case that all their employees would be working as searchers, it would not be possible to get those results by their own.

Although the development of artificial intelligence is currently one of the main priorities in governments and organizations (European Commission, 2020), we cannot ignore its difficulties and challenges (Brundage et al., 2018). The people responsible for these systems and the leaders of those organizations in which they consider making decisions based on "deep learning", must ensure the maximum accuracy and precision of the information systems, eliminating prejudices, biases, or erroneous judgments, that could be developed through artificial neural networks, as stated in the report *Bias in Algorithms – Artificial Intelligence and Discrimination* by the European Union Agency for Fundamental Rights (2022).

Without being too exhaustive, but aware of the diversity of industries and robotic applications, in the field of human-robot interaction, we must also present novel formulas of robotization and interaction of a more tangible nature, such as **state-of-the-art robots, soft robotic suits** and **cyborgs** that, as emerging technologies, are sure to monopolize technological markets in the coming years (Luke, 1997; Pelegrín-Borondo et al., 2017; Xiloyannis et al., 2022). Among many other trends, technologies have evolved from external devices (laptops or smartphones) to devices or technologies that humans can dress like any other accessory: watches or smart glasses (wearable technologies); currently evolving from these aforementioned wearable technologies to devices implanted in their own bodies or "*insideables*" (Olarte-Pascual et al., 2015). How would be the human-machine interaction when the machine is already part of your own body? This question is generating a huge interest and from multiples perspectives like ethics, health, safety, data ownership or privacy among others (Gauttier, 2019; Olarte-Pascual et al., 2021; Viseu, 2003). These specific technologies at work, brings some new elements if compared to other ways of robotization. These devices represent additional challenges for the employee, in the sense that the human lose control over the device, being inserted on permanent basis, as well as representing potential conflicts with employee’s body functions (Gauttier, 2019). For the moment, companies like Epicenter[10], Three Square Market[11] and New Fusion[12], invited to their employees to insert a chip for "convenient" purposes like password, badge access and payment solutions (Gauttier, 2019). On average, less than 10% of their employees decided to participate. That chip didn't provide any functionality related to work performance, and participation was on voluntary basis (for the moment). Considering the higher turn-over rate in new generations (Ng, E. S. et al., 2010), would be the employees open to undergo surgical interventions for each new employment? Maybe for some of them, being exposed to a new surgery for each new employer, becomes an additional reason to stay and not to leave their current employer (Gauttier, 2019).

Regardless of the technology used, we can observe that depending on the casuistry that may occur in each organization, we can talk about environments merely oriented to the task (Hawryluk & Rychlik, 2022; Semin et al., 2020), or complex robotic systems that require a greater organizational effort, paying attention as well as to communication between the employee and the machine, and determining those competencies that employees will require to interact properly under those circumstances (Garsombke & Garsombke, 1989; Kim, Y. et al., 2022; Noro & Okada, 1983).

In this sense, people's mind is usually configured in relation to events already lived (previous experiences). In the case of robotization, this principle may be inappropriate, because despite most of the employees have exposure to robots in other

[10] Epicenter is a Swedish consultancy firm with 2000 employees worldwide.

[11] Three Square Market is an US company (microchips producer).

[12] New fusion is a Belgian digital marketing and tech firm.

contexts, it does not mean that the interaction with robot at work would be positive nor effective.

What is clear, is that before that interaction, it would be needed a previous and proper training. Let us think in this sense, how traumatic it is for most elderly people, to adapt a new technology, without having received adequate training or previous exposure.

Having analyzed business cases related to robotization adoption in companies (Segura et al, 2021), has been determined four structural components which determines the model of Human-Robot collaboration: The level of interaction; the different types of roles; communication interfaces to allow interaction and safety control modes.

In terms of **level of interaction**, there is a huge amount of disperse literature, but as context for current research, it is highlighted the below classification.

Table 2.5 Levels of interaction Human-robot

Independent	Human operator and robot work on separate workplaces and detached from each other.
Sequential	Human operator and robot work on consecutive processes on the same workplace at a separated time.
Simultaneous	Human operator and robot work on separate processes on the same workplace at the same time.
Supportive	Human operator and robot work synchronously to complete a common process on the same workplace.

Source: Segura et al. (2021); Cesta et al. (2016); El Zaatari et al. (2019).

According to the type of **work roles**, there are multiple classifications, most recently the one developed by Segura et al. (2021) which was based on Bratman (1992). They refer to three different work roles: supervisor (master role), peer (mutual setting) and subordinate (robot has the master role). Particularly for this dissertation, it has been chosen an extended version from Scholtz (2003), in the sense the author has added a mechanic/programmer role, having split as well, the peer role into a bystander and peer role. This model offers a wider scope, mainly for industrial environments. This has been the classification included into the questionnaire of this dissertation.

Table 2.6 Work roles in the Human-robot interaction

Supervisory	The human operator takes the master role in the master-slave relationship.
Operator	The human work "inside" the robot, operating to modify abnormal behavior or to take control.
Peer (teammate)	Huma operator and robot mutually set or follow the pace in a given task.
Mechanic or programmer	When human needs to adjust physical components or adjust program settings.
Bystander	Human does not interact with the robot but needs references from robot behavior to understand consequences and context at work.

Source: Scholtz (2003); Segura et al. (2021) based on Bratman (1992).

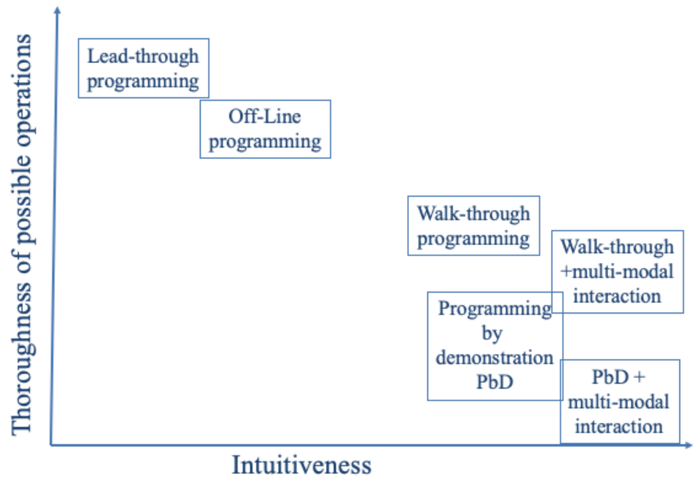
Following Segura's distinction (2021), we should distinguish as well depending on **communication interfaces**, currently offering a more human-friendly language than in the past (Villani et al., 2018), bringing up to a multi-modal interface, which can combine multiple ways as described in Figure 2.14, but just applying to programmers. This review is relevant, mostly considering the current development of physical robots, Artificial Intelligence, as well as other modalities in terms of pure software-robot.

As per Villani et al. (2018), the lead-though programming mode represents a classic model where the robot's control is under a "teach" mode and trajectories, endpoints and functionalities are recorded into its memory to be reloaded and playback later on. An advanced model would be the known as OLP or Off-Line Programming, what means a remote simulation of the specific tasks in a 3D model. Once configured, the program should be exported from the computer (simulator) to the robot.

Next level in terms of intuitiveness, it would be the walk-through programming which allows to program without any knowledge of programming language because the user can physically move the robot, and everything is recorder as a task to be performed in the future.

Programming by demonstration (PbD) allows interacting physically with the robot, but at the same time, robot may apply a certain artificial intelligent to learn from movements, making possible that it would generate own solutions under varying conditions.

Figure 2.14 Approaches to the programming of industrial robots



Source: Villani et al., 2018

All these ways to program robots can be complemented with multi-modal interfaces, what brings human-friendly capabilities to the robot, such as gesture, facial expression among others, facilitating incredibly the task of programming to the user.

And these multi-modal interfaces or communication interfaces can be summarized in terms of: (1) body gesture interfaces, based in vision systems that process human operator body gestures and physical movements into instruction commands. (2) facial/eye tracking, which vision systems process human operator facial expressions and eye activity (i.e., blinking, gazing) into hands-free instruction commands. (3) voice command, supported on speech recognition systems that process human operator natural language into hands-free instruction commands. (4) haptic interfaces, considering robot hand-guiding features that are used for interacting, notifying, and teaching instruction commands and (5) traditional interfaces, based on widely adopted hardware such as buttons, keyboards, mouse, or monitors used for data input or output (Segura et al., 2021; Villani et al., 2018).

And the last factor to be considered in terms of HRI, is the **safety control mode**, which in addition represents an official requirement from the International Organization for Standardization norms. According to ISO 15066 (latest edition 2016), the classification of safety control modes is the following:

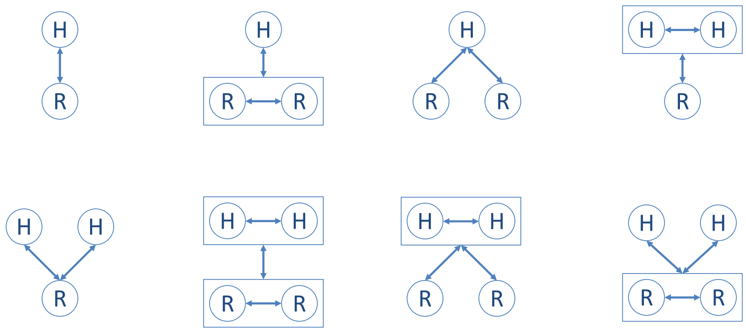
Table 2.7 Safety control modes (ISO 15066)

Safety monitored stop	The robot is stopped immediately from any movement if a human operator enters a pre-designated safety area of the workstation.
Hand guiding	The robot is enabled to be manually controlled by a human operator without the need of extra devices or control interfaces.
Speed & separation monitoring	The robot work area is divided into safety zones where both speed and distance are followed and adjusted based on the human operator's location.
Power & force limiting	The robot is programmed to work within certain levels of force and torque constrained by biomechanical load limits where damages or injuries are not expected to be caused in human operators.

Source: International Organization for Standardization, ISO 15066 (2016) .

But beyond the data at the macro level, it should be noted that the degree of robotization differs significantly between companies, even within the same sector of activity, generating ratios (number of employees / number of robots) of different kinds, this being a key issue, to the extent that this ratio influences the type of interaction of workers with devices (Yanco & Drury, 2004). Likewise, in case there are several robots in a certain organization, we must analyze if these robots are of the same type or respond to different categories, considering that the interaction in teams with different robots is more complex especially in relation to the management and consolidation of information for decision making (Yanco & Drury, 2004). On the other hand, if several humans interact and/or direct the same robot, organizationally it must be determined if the employees agree in advance on the instructions and direction provided to the robot, or if on the contrary it is the robot that has the capacity and has autonomy to prioritize and clarify potential conflicts in the instructions received. In the same way, you can also find models in which different robots receive different instructions and robots must elucidate by themselves. All the casuistries respond to the robotic classification based on the type of interaction, and as shown in Figure 2.15, they can represent high degree of variability with the consequent complexity of human-robot management.

Figure 2.15 Combinations of single or multiple humans and robots



Source: Yanco & Drury (2004)

Considering all the scenarios previously exposed, where **H** corresponds to human/employee and **R** corresponds to robot, we find a multitude of scenarios that lead to different roles that an employee can assume in the organization.

According to Scholtz (2003), we remind the different roles of: *supervisor* when he gives a certain instruction (objective) to the robot and it carries it to term; the *direct operator* of the robot interacts more continuously with the robot, trying to alter the behavior if it is not adequate or adjusting functions; in the case of employee as *a teammate* together with the robot, the tasks are shared in such a way that the employee performs a series of tasks or part of them and the robot others, all forming part of a common goal; as for the *mechanics* or *programmers* of robot would correspond those tasks of repair or change of the hardware or software of the robot.

Finally, the *observer* or *bystander* should not perform any tasks with the robot, but nevertheless should be aware and knowledgeable of the robot's activity, as they at least share a space.

As shown in this paragraph, even in the case of observers, it is very common for employees to share physical space with robots, so it is not surprising that there are authors (Hüttenrauch et al., 2006) who present a classification of robotization (not robots) based on the type of proximity or physical interaction that can occur between the worker and the robot, and that can vary from the one that avoids contact, the one that corresponds to a passing interaction; a mere accompaniment on the route; approach or even direct and frequent contact.

All this, brings an additional classification based on terms of **space-time** of robotic activity (Ellis et al., 1991): a distinction is made between the *spatial dimension*, which takes reference to those tasks or functionalities that are happening in the same place, and those that separate the location of the collaborators (person and machine); and on the other hand, the *temporal* dimension that distinguishes between synchronized (happening at exactly the same time) or asynchronous functions when that condition is not met.

Table 2.8 Time-Space taxonomy

		TIME	
		SYNCHRONOUS	**ASYNCHRONOUS**
SPACE	**COLLOCATED**	Electronic Meeting-rooms Wheelchair robot	Computer-assisted crisis management Mars Rover (to explore Mars) Robots in the factory
	NON-COLLOCATED	Videoconference Rescue robots	email

Source: Ellis et al. (1991); Yanco & Drury (2004).

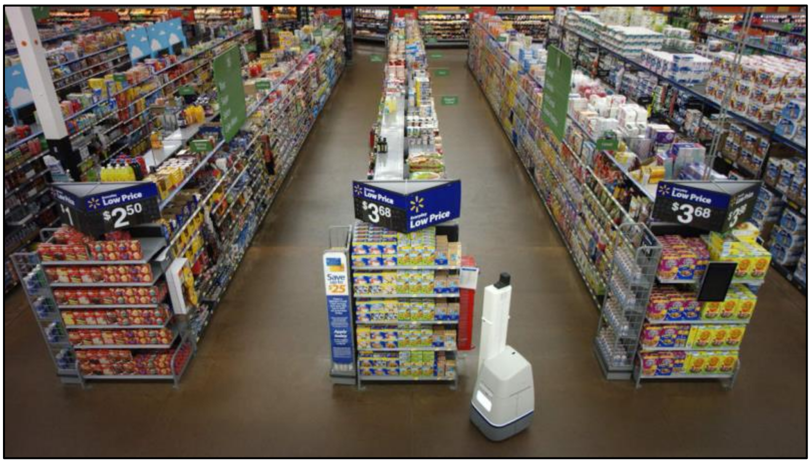
Another distinction that we can find would be based between purely industrial companies and B2B (Business to Business) companies, with those B2C (Business to Customer) companies that provide service or deliver products directly to the final consumer. This distinction **depending on the business model** can determine the type of robot or robotization that the company chooses, with the aim of positively or neutrally influencing the perception of some stakeholders (usually customers or employees).

For example, we can point out that the Walmart distribution chain does not want robots to have a humanoid shape, so that the devices are perceived only as a tool more than anything else, a criterion that corresponds to the morphological differentiation of robots presented by Fong et al. (2003).

However, the best way to facilitate the changes is to proceed gradually, so that the user becomes aware little by little, and the implementer of the technology also improves along his/her learning curve when integrating it into work systems (Cesta et al., 2016). That was the methodology applied in the case of Walmart, already introduced it in this chapter, that has been robotizing their facilities for years, initially incorporating robots only in 50 of its stores during 2017, to end two years later, implemented these systems in 350 stores (Pérez, 2019) .

These were non-intrusive robots (Bicchi et al., 2008; Hüttenrauch et al., 2006) that perform routine and high-precision tasks such as the control and replenishment of stocks, sharing space with customers while they are shopping. This is one of the main reasons why device’s design is important (Wickens & Kramer, 1985; Wickens et al., 2013).

Figure 2.16 Robot in retail store



Source: Bossa Nova (2019)

The most effective organizations try to manage the implementation of robots in a very systemic way and the technological developers of the robots must listen carefully to the requirements and concerns of their customers (Kim, Y. et al., 2022). As is the case of Bossa Nova, a company that develops robots for large facilities, for which, although their robots do not have humanoid appearance, they incorporate "eyes" so that the client or employee who shares space with the robot, always know the direction of movement that the robot takes (Hollon & Rogol, 1985; Noro & Okada, 1983).

With the technological revolution that has spread through all sectors, but in some such as the financial sector, it has done so in a very accentuated way (Mhlanga, 2020; Nain & Rajan, 2023), making it almost mandatory that even the client has technical knowledge to be able to operate in this area. A very significant example of this trend is the development of Fintech companies based on "apps". In these new developments, the customer must be able to use basic computing devices to extract and understand their financial information, as well as subsequently to make decisions. The most important drivers for the acceptance of this new technology are perceived trust and reliability, as well as transparency and financial literacy (Jünger & Mietzner, 2020).

In the field of human-robot interaction and transcending a mere physical interaction (Onnash & Roesler, 2020), it should be noted that organizations must carry out a very careful implementation of the so-called "***deep learning***", especially applied in decision making (Jarrahi, 2018). The implementation of such conceptually and intellectually complex systems must be designed to provide benefits for all stakeholders (Helm, 2011), because otherwise unforeseen responses can be generated even by the deep learning algorithm, with consequences that can be critical (Im et al., 2008; Sorokac & Rigali, 2019). The fact that the system has huge amounts of information should provide employees with more opportunities in their day to day (Goodhue & Thompson, 1995), positively impacting both the performance expectation (PE) and reducing the expectation of effort (EE). In this sense, it is worth mentioning some principles that should guide a successful implementation of artificial intelligence and "*deep learning"* systems (Winston, 1992):

People **need to know** what deep learning is, how it works, and how it can affect their work. Responding also to all the principles and requirements in terms of confidentiality and privacy for all stakeholders (Lynn et al., 2016). It must be considered that an extraordinary amount of data will be generated and managed, and it is essential that trust is generated in relation to its treatment, responding to all the requirements of the new European Directive of Personal Data Protection.

Employees and stakeholders, including potential customers, must **be able to understand** how any "*deep learning*" system comes to make decisions and how humans manage the proposals carried out by the machine (Lee, M. K. et al., 2015). In short, it is not about explaining how the machine works, but how people work with what the machine does.

In the same way it is important that people "unlearn" to free themselves from false beliefs, limitations or simply remove vices (Hedberg, 1981), "*deep learning*" must also **unlearn** certain knowledge or data, in order to protect against unwanted biases from the set of available data (Mehrabi et al., 2021). This is known as "reversibility" and must be designed in the conception of the project of implementation of any artificial intelligence (Ryan & Stahl, 2020).

2.2.3 Benefits and conflicts

In general terms, there are a number of preconceived ideas about the figure of the robot. Which can vary from recognizing them as a mere utility to develop competitive advantages (cost reduction, speed, quality…), being able to perform our own work or another type of work, or even the origin of labor force reduction (Argote et al., 1983).

Traditionally, three reasons have been determined why automation could be carried out (Wickens et al., 2013): first, to carry out dangerous functions or tasks that correspond with the three Ds (dirty, dangerous and dull), such as handling radioactive materials, work in depth, in outer space or simply carrying out tasks that a human could never perform (Takayama et al., 2008). Secondly, it is proposed for those tasks that to a certain extent are likely to be performed in the wrong way by people, mainly because of the high workload they imply, or because of the fatigue or boredom that these may generate (Jacob et al., 2023). And last but not least, to complement the perception, memory, attention, or motor capabilities of the human (Jacobs et al., 2019; Ng et al., 2021).

Since robots had originally fallen into the first two categories (Wickens & Kramer, 1985), it is reasonable to assume that people would logically predict the substitution of humans by robots. However, production operators are being replaced in tasks that are neither significantly intricate nor hazardous. Remarkably, these tasks are ones that humans can effortlessly and safely carry out without any difficulty or risk. (Chui et al., 2016). It is important to note, that in most cases, such robots still need to be supervised. This is important in terms of HRI, and employee's motivation to accept such robotization.

When discussing **robotization or robotic automation**, it typically refers to the implementation of robots in industrial or business processes, aiming to replace functions traditionally carried out by humans. In fact, from an economic perspective, automation is also understood as the development or adoption of new technologies that allow transform capital into labor for a series of tasks (Acemoglu & Restrepo, 2019).

The objective of this research goes beyond private environments and organizations focused on producing goods or services. It seeks to encompass government organizations as well, recognizing that public administrations have increasingly embraced and must continue to embrace robust digitalization processes (Dunleavy et al., 2006). Some drivers for the governments to automatize, could be cost reduction, as well as the improvement and speed providing services. In that sense, Covid-19 pandemic has been a perfect trial to examine the digitalization and automation processes of public administrations, bringing new protocols for interaction between the administration and the administered.

This research centers around the topic of robotization and robotics, with a particular focus on the growing interest in these fields from social and management perspectives. Over the past ten years, there has been a noticeable rise in academic attention given to both terms, indicating the progression of publications in the humanities and management domains. To better demonstrate the significance of the terminology, it has been determined that the bibliographic search will be expanded to include the term "robotics" as an additional alternative.

Table 2.9 Articles including "robotization" or "robotization + robotics" as topic

	Robotization			Robotization + Robotics		
Publication Year	**WOS**	**SCOPUS**	**% variance vs. year before**	**WOS**	**SCOPUS**	**% variance vs. year before**
2022	90	72	3%	222	249	41%
2021	94	64	3%	134	201	-2%
2020	90	63	94%	132	210	19%
2019	55	24	46%	112	176	55%
2018	38	16	170%	92	94	17%
2017	15	5	82%	88	71	14%
2016	7	4	10%	89	50	26%
2015	7	3	233%	69	41	-38%
2014	2	1	0%	66	111	99%
2013	2	1	200%	52	37	14%
2012	0	1	0%	56	22	-3%
2011	0	0	-100%	56	24	11%
2010	1	1		54	18	

Source: ISI Web of Knowledge and Scopus databases (2023).

Furthermore, depending on the particular aspect of the dissertation, additional concepts such as automation and digitalization have also been considered.

Automation, a concept linked to the robotization process, is one that refers to a workflow, in which information or task (concrete action) passes from one point to the next according to a procedure established and controlled by an information system, using automatic equipment (Stohr & Zhao, 2001). Dictionary defines automation as "the technique of making an apparatus, a process, or a system operate automatically" and the International Society of Automation describes it as "the creation and application of technology to monitor and control the production and delivery of products and services" (International Society of Automation, 2023). When the terms robotization or robotic automation are mentioned in this research, they typically refer to the implementation of robots in industrial function or business automation processes, albeit with varying characteristics or attributes.

However, the concept associated with the administrative or office environment increasingly present in our days, comes from 1970 when it referred to the reduction of paper and elimination of repetitive tasks (Stohr & Zhao, 2001), and linked to corporate social responsibility, such as the decrease in the consumption of natural resources (Ng et al., 2021), costs, in addition to removing repetitive tasks and reducing waiting times (Olmstead & Rhode, 2001). In that sense, as an additional positive aspect, mentioning that long-term exposure to monotonous or low-value tasks can lead to employee fatigue and dissatisfaction (O'Hanlon, 1981).

Digitization consists of a mere translation into bits of any element (Becerril-Gil & Ortigoza-Limón, 2018). This implies the capability to transform various types of files such as documents, music, images, and social media content into a computer language. Furthermore, it involves the valuable task of organizing this information collectively and analyzing it using the technique known as Big Data Analytics (Lehrer et al., 2018). As a reference and to take perspective on this topic, it should be considered that the analysis of faces and behaviors in social networks, it allows analyzing feelings, emotions and reactions. At this point, it is also relevant to indicate that the incorporation of all types of input, through digitalization, it is an essential vehicle that serves to the "machine learning", to carry out its own developments, exponentially projecting the capacity of intelligence or knowledge of computers and consequently, robots.

At present, our focus is on examining the process of robotization, including its different forms. It would be advantageous to offer a more comprehensive elucidation of the distinct phases encompassed within these processes, analyzing the stages of acceptance at workplace that may apply to all different processes (Acemoglu & Restrepo, 2019; Autor, 2019; Frey & Osborne, 2017). The World Economic Forum, specifically in the article written by Wise (2018), outlines five distinct stages of acceptance in relation to AI, which can be extrapolated to encompass all types of robotization.:

1. **Fear:** when an organization chooses to adopt a robotic solution, it is a rational response considering a negative reputation often associated with robots. It becomes crucial to inform employees well in advance about the implementation, providing clear details regarding the specific tasks that robots will handle (as well as those they will not).
2. **Apprehension:** At this point, employees are not primarily concerned about job security, but a new question arises in their minds. They start wondering whether they possess the necessary skills to effectively work with the robot. It is crucial at this moment to prioritize providing the required training to ensure that employees have the necessary competencies to fulfill expectations and perform their roles to the best of their abilities.
3. **Curiosity:** about how the "machine" reacts under unexpected scenarios or situations. Is the moment, where the human is positioned in a higher role, testing and knowing better how the robot works.
4. **Tolerance:** After few weeks, the employees become accustomed to their behavior, recognizing contributions and failures. At that time, the employee can propose measures to improve and solutions to specific issues.

5. **Satisfaction:** Once employees acknowledge that robots are an integral part of their work environment and positively contribute to their performance, they begin to perceive them as valuable tools and teammates. They recognize how robots enhance their daily work reality. At this stage, it is crucial for management to openly share Key Performance Indicators (KPIs) to demonstrate how this new reality with robots actively contributes to improved outcomes and better overall results.

In the upcoming sub-chapters, will be included two factors that impact people's perception of machines and shape human-machine interaction within the context of robotics analysis. Firstly, we will explore the positive aspects of robotization from a humanistic standpoint, examining how it can be beneficial. Secondly, we will delve into the negative or potentially harmful aspects that robotization may introduce to the labor environment and society as a whole.

2.2.3.1 Social benefits of robotics

There are a lot of different positive aspects from robotization, directly impacting from a social perspective. Elements like the development of new skills and competencies of employees, as well as improvement in terms of safety at work, more efficient decision-making processes, and of course implications in terms of financial profits, supply chain optimization, reduction in terms of energy and lesser raw material consumption and consequently, quality and production cost reduction (Cascio & Montealegre, 2016).

From a demographic perspective, according to the Department of Economy and Social Affairs of the United Nations, elderly population will reach 21% in 2040, with the consequent implications in health and care systems, requiring more quantity and qualification of caregiver personnel (Pinto et al., 2010).

According to the report "*Solutions for the chronicity*" of SEDISA[13] (Sociedad Española de Directivos de la Salud, 2015), above 70% of the costs of a healthcare nature in Spain were directly or indirectly related to chronic diseases. Therefore, investments in autonomous surveillance of these diseases have continued to grow. It should be noted that monitoring outside the hospital has become a crucial factor in the future of medicine. Based on this, robots will play a decisive role in ensuring the sustainability of this new model, particularly in increasing care for the elderly and individuals in need of continuous assistance (Khosravi & Ghapanchi, 2016). Technology has the potential to improve the lives of individuals with disabilities and provide support to the staff assisting them. In this regard, it is worth mentioning the activities of foundations such as the *Instituto de Robótica para la Dependencia*, which connects robotics with groups requiring special care, such as the elderly and individuals with disabilities.

Nevertheless, some barriers still pending to be afforded, like difficulties to interact with technology, feeling of stigmatization (users) and some ethical questions remain among users and workers in this field (Wu et al., 2014).

Closely linked to the previous phenomenon, we find the relationship between **robotization and retirement pensions**. One of the most recurring questions… *if robots work, who will contribute to pensions?* The answer to this question is even more complex if we consider that the baby-boom generation still active and that many millions will retire in masse at once. In opinion of Marco Salvi[14] of Avenir Suisse[15], "*on that moment, will be generated a very important talent gap in our labor market. And if there is no talent*

[13] Spanish Association of Managers in Health Institutions (Sociedad Española de Directivos de la Salud).

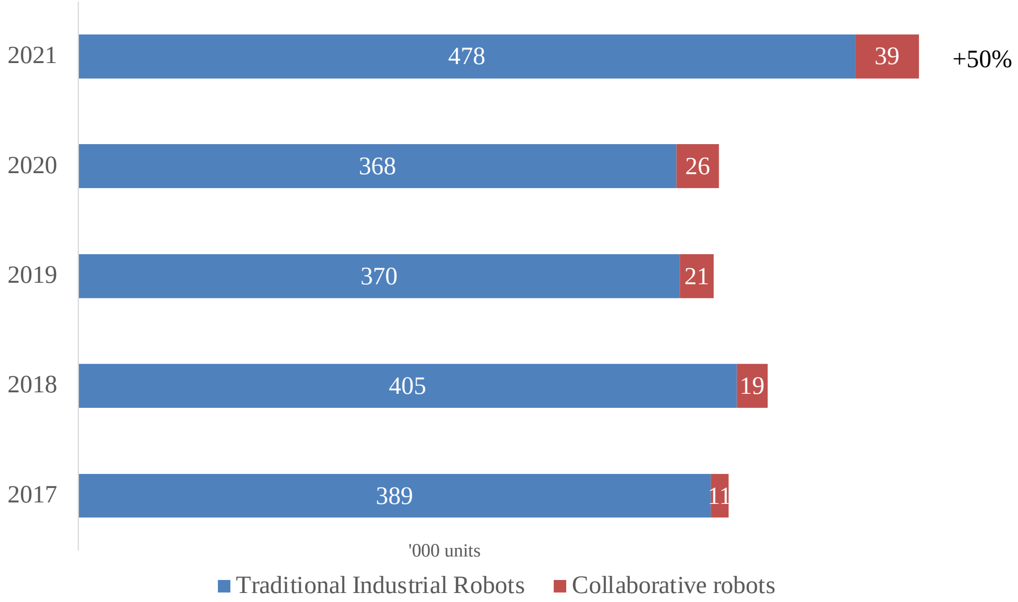
[14] Marco Salvi is Senior Fellow, Head of Research Equal Opportunity Society at Avenir Suisse.

[15] Avenir Suisse is a Swiss think tank for economic and social issues, supported from all economic sectors and regions of Switzerland.

working and producing, neither is GDP quoted nor generated". In this direction, it should be noted that Japan and Spain are countries that will face this challenge (Ministry of Health, Labour and Welfare -Japan-, 2018; Directorate-General for Economic and Financial Affairs -EU-, 2021). Population in both **nations is aging rapidly**, and the birth rate is below the replenishment rate. If we add to these factors the legal restrictions over migration, the demographic projections are not very encouraging. In fact, countries like Germany or Japan, are already covering thus **lack of personnel** with robots (Funk, 2014). To afford these issues (increase of retirement pensions' beneficiaries and reduction of labor force), according to Bogataj et al. (2019), there are four alternatives (not necessarily exclusive): **(1)** to consider additional pension schemes, to compensate the lack of capabilities of their older workforce; **(2)** to hire new migrant and younger employees; **(3)** offshoring production to countries with younger workforce; **(4)** to improve ergonomic conditions and put in place collaborative robots to contribute to better labor conditions to older workforce.

Regarding this fourth point, as per the data provided by the International Federation of Robotics (2022), the majority of robots that have been installed in the past five years are of the "traditional" type. Even though there has been a notable increase of 50% in the number of collaborative robots in 2021, they still constitute less than 8% of the overall robot installations.

Figure 2.17 Evolution of collaborative and traditional industrial robots



Source: International Federation of Robotics (2022)

Another of the functionalities to which society recognizes robotization a great potential, is **saving lives** (Bogue, 2023; Manyika et al., 2013; Robinette et al., 2017). In this field there are many initiatives and devices already underway, along with many others that will most likely appear in the short term. This dissertation shows some of the most representative, such as the SearchWing project of the Augsburg University of Applied Sciences, which aims to build a rescue drone that helps to better find shipwrecked refugees in the Mediterranean (Hochschule Augsburg, 2023). This ultralight drone takes pictures and returns to the rescue ship. With a range of 100 kilometers, in a round trip of 60 minutes, the plane can shoot more than 2,000 photos that are reviewed.

Another related initiative is "Auxdron", the drone which delivers life jackets to any point in the sea (Bogue, 2023). For the moment, it is not a fully autonomous device, requiring a lifeguard to handle it remotely, Auxdron can fly up to 80 kilometers per hour and has an infrared camera that makes possible to locate people to be rescued. Following with the latest devices with such functionality, "Deep Drone 8000" has been developed by the United States Navy and it dives to 2,500 meters depth, in order to be able to evacuate a submarine in case of need. These are some examples of many other initiatives and projects underway (Bogue, 2023).

And of course, it should be mentioned the role of technology, robotics and AI, for the development of new vaccines during COVID-19 (Murphy et al., 2020). Automated and robotized processes have allowed to accelerate development and testing phases. As example, the incorporation of ABB[16] robots at Mahidol University (Thailand) for the development of the COVID-19 vaccine. Researchers in charge have relied on robots, because the testing of a vaccine is a repetitive task, which causes a lot of stress, both physical and mental fatigue. And probably the most relevant on those days, the risk of infection (Sarker et al., 2021).

In this specific case, researchers from the university together with the Institute of Molecular Biosciences, developed an AI-Immunizer system which used a six-axis robot and a dual-arm to execute the entire operation. Thanks to this technology, the testing offers maximum reliability, by carrying out high precision actions with fewer errors, without interruptions and without infections (ABB Robotics, 2021).

[16] ABB Robotics is a pioneer in robotics, machine automation and digital services, providing innovative solutions for a diverse range of industries, from automotive to electronics to logistics. One of the world's leading robotics and machine automation suppliers.

Figure 2.18 ABB robot supporting vaccine development (COVID-19).

Source: ABB (2021).

Delving into the field of health, robots are also decisively influencing the extension of life expectancy (Manyika et al., 2013). In 2016, the achievements of STAR, an acronym for Smart Tissue Autonomous Robot, demonstrating an autonomy that allows to operate without human intervention (Shademan et al., 2016). The system consists in a combination of 3D vision, infrared light and a suture algorithm with the most relevant surgery techniques. Another element are the nano-smart biodevices, that in the words of Dr. Samuel Sanchez[17] "*can help overcome the limitations of conventional robotic systems, such as flexibility, responsiveness and adaptability*" (Escribano, 2016). In this instance, the term "device" is used instead of "robot" since the item being developed can encompass various elements such as materials, substances, or articulated components, rather than strictly being limited to a traditional robot (Lorca, 2021).

In contrast, a recent development known as xenobots has surfaced. This term is a neologism combining "xeno", derived from the African frog (from which its cells are

[17] Head of research at IbEC Bioengineering Institute of Catalonia (Spain)

sourced), and the suffix "bot," indicating that these entities can be programmed to perform particular tasks (Coghlan & Leins, 2020).

All these developments together with some others which are primary based on data management, are framed within the so-called "healthtech" (Chakraborty et al., 2021). Without mentioning specific initiatives, just to mention that "big data" and automated processes, will be decisive in the improvement of medicines and its consequent long-life expectancy. According to Maria Rodriguez[18], "*Artificial intelligence has the potential to be applied to almost any field of medicine, drug development, as well as patient treatment and monitoring*" (Zarzalejos, 2020). In this sense, the purpose of IBM is to bring “Watson” (artificial intelligence product), into health treatments. "*This technology, together with available records, allows to automatically identify problems in medical records, summarize the history of care and offer specific reports, being able to predict if a patient who has suffered breast cancer may have a relapse in five years after his/her first treatment*" (Zarzalejos, 2020).

Drawing upon various technologies and advancements for physical/material solutions, individuals affected by conditions such as multiple sclerosis, cerebral palsy, or stroke, perceive an exoskeleton or an exosuit (robotized device) more than just a device; they perceive the opportunity for a whole new life. And of course, bringing opportunities in terms of safety at work and productivity for employees (Butler & Wisner, 2017).

[18] Researcher at IBM's Zurich Research Institute.

Figure 2.19 Exoskeleton · Exopulse Mollii Suit©

Source: ©Ottobock SE & Co KGaA (2021)

The Exopulse Mollii Suit© (2009) is a full body exosuit with 58 embedded electrodes that fires 20 times per second with tailored electric impulses to treat mobility issues. Officially, it is recognized as a novel, near-full-body neuro-stimulation spasticity therapy tool that is drug-free and non-invasive. According to Fredrik Lundqvist[19], this device is a wearable robot (Ottobock, 2023).

When discussing the enhancement and preservation of human lives, it is essential to address the crucial role of **nutrition**. Robotics also influence on it, through technological advances in agriculture and livestock (Olmstead & Rhode, 2001; Rasmussen, 1982; Rovira-Más, 2022). These developments are decisive to reach amount and quality of nutrition in society, especially considering the incessant population growth, especially in Africa and Asia (United Nations, 2022).

Farmers have to address challenges related to irrigation, pests, lack of workforce (Rasmusssen, 1982). And most of these issues have had to be addressed either

[19] Founder and inventor at Exopulse Mollii Suit. Swedish MedTech company focused on innovation in the field of full body electrostimulation.

incorporating heavy machinery or using chemical products (Nidumolu et al., 2009). In the long term, both solutions are unsustainable both from an economic and environmental perspective (Chauhan et al., 2022).

Food and Agriculture Organization (FAO) has expressed concerns about land degradation. According to the FAO, approximately one-third of the world's land is considered to be severely degraded. This degradation is primarily caused by factors such as erosion, chemical pollution, over-fertilization, deforestation, and unsustainable agricultural practices (FAO, 2017).

Land degradation has significant consequences for agricultural productivity, food security, and environmental sustainability. It reduces the soil's fertility, impairs its ability to retain water, and increases the risks of erosion and desertification. These factors can lead to reduced crop yields, loss of biodiversity, and increased vulnerability to climate change. With this picture, it seems that new technologies may help in terms of risk assessment, fertilizers' rationalization and weather forecasting (Saiz-Rubio & Rovira-Más, 2020). Scanners in the field allow to detect plagues and determine the amount of water to be supplied -and not more than needed- (Rovira-Más, 2022).

Figure 2.20 Field scanalyzer

Source: Robotics & Automation News (2020)

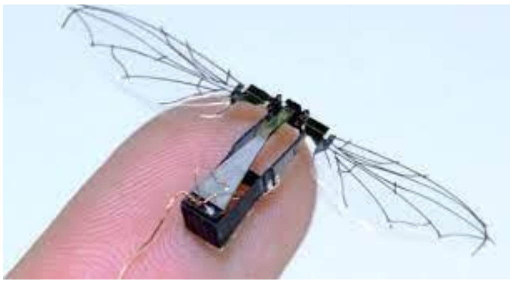
Certain robots are already recognized as actors that contribute to the development of organic agriculture, as for instance in the United States, the devices developed by the company Carbon Robotics, are recognized by the Public Administration as allowed for large organic agricultural farms.

Figure 2.21 Autonomous weeder

Source: Carbon Robotics (2021)

Drones, derived from the Anglo-Saxon term for male bees, are aerial devices capable of autonomously performing various tasks. In Japan, the National Institute of Advanced Industrial Science and Technologies has developed drones that facilitate pollination through the use of a sticky gel with ionic properties (Ponti, 2017). A North American counterpart to these drones is the "RoboBee," which has been developed by Harvard University after 12 years of research depicts both models (Wyss Institute, 2019).

Figure 2.22 Japanese Drone Bee and US Robobee



Source: NIASTH | Bloomberg (2016) **Source: Harvard University | Clipset.com (2016)**

Beyond this above mentioned technology, the field of artificial intelligence and algorithms are helping as well to take care of the **environment,** with the purpose of managing extremely complex environments, increasing efficiency and sustainability (Ng, K. K. H. et al., 2021). For example, the forecast of the energy that will be supplied by a solar power plant is very important to define the operational strategies that guarantee the storage and supply capacity of such energy. This task requires advance knowledge of adverse phenomena, such as cloudiness, in order to plan in the most effective way the production of energy in each installed plant (Afarulrazi et al., 2011).

Likewise, in order to manage in the most efficient way the materials of the facilities (glass of the mirrors and general energy receivers), it would also be a matter of reducing thermal stress as much as possible, anticipating the drastic drops in energy by carrying out the progressive blurring of mirrors, to maintain their integrity (Alonso-Montesinos et al., 2019). Through a series of algorithms, a prediction of solar radiation is offered in the short term, up to three hours and estimates the amount of energy that will be produced at each moment, allowing a more accurately knowledge of the electricity production fluctuations, which allows a better control of the storage of the energy that is generated (Afarulrazi et al., 2011).

In the realm of the environment and in line with the United Nations Sustainable Development Goal 12.3 (SDG), which aims to reduce food waste, it has been observed that Europe alone wastes around 50% of the food it sells (FAO, 2011). In this context, the integration of artificial intelligence into household kitchens, restaurants, and healthcare institutions is demonstrating its potential in minimizing the wastage of food resources. An example of such AI implementation is the device created by Winnow[20], which has enabled its customers to save a staggering 23 million meals annually (Lebleu, 2019).

Contribution to real gender equality: Undoubtedly, there is potential for examining how robotization will contribute to the elimination and redistribution of tasks between humans and robots (Winfield, 2017). In that sense, as domestic robots become more prevalent, they are expected to reduce the workload of domestic assistants (Bryson, 2010). And obviously, this advancement presents a new paradigm that could relieve women from certain domestic responsibilities that have traditionally been assigned to them, as suggested by Levy (2006). In terms of equal opportunities, as some jobs that required extreme physical effort, were traditionally assigned to men (Jacob et al., 2023), nowadays can be occupied by women.

Safety and health at work: Without any doubt, this is a key positive aspect of robotization (Bicchi et al., 2008; Lee, J. et al., 2019). In the sense that impacts on the reduction of those jobs for human which implies physical risk, too much physical requirement (Jacob et al., 2023), hazardous tasks (Acemoglu & Restrepo, 2019; Chui et al., 2016).

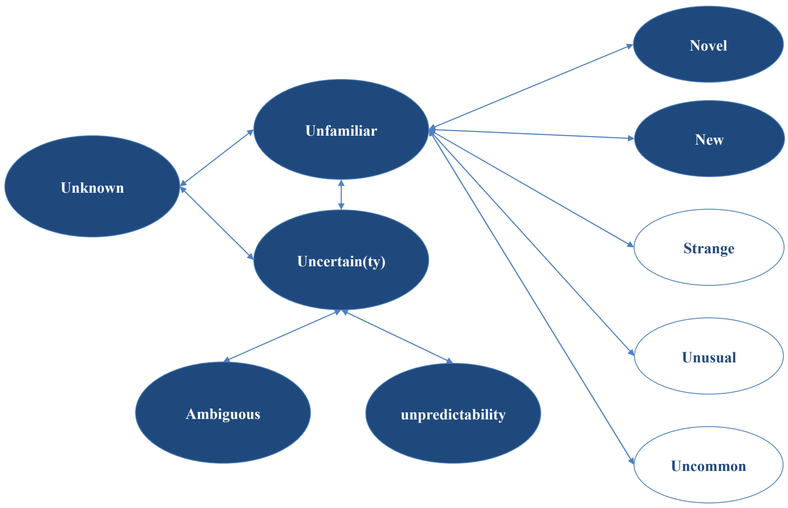
[20] Winnow is part of Compass Group Belgium, a technology company which develop solutions to save meals from the bin.

2.2.3.2 Conflicts, ethical and philosophical considerations

Since the beginning of robotics and even from the beginning of the science fiction, the concept of robot has aroused some suspicion and concern about its potential and evolution (Asimov, 1950). And these feelings and reactions are normal, because as Lovecraft already advanced in 1927 "*the oldest and strongest emotion of mankind is fear, and the oldest and strongest kind of fear is fear of the unknown*" (Joshi & Schultz, 2001).

Thinking about robots, it can be perfectly understood the reasons for such fear. Mainly considering the concept of "unknown" as the perceived absence of information at any level of consciousness, and merging some additional constructs as proposes Carleton (2016).

Figure 2.23 Fear of the unknown and its constructs



Source: Carleton (2016)

Following with Carleton's model, despite people interact even unconsciously with robots (Vinjamuri, 2023) based on current "robonomic" economic system (Crews, 2016), they can still be considered as **unfamiliar** (Reich-Stiebert & Eyssel, 2016). There is too much information about its implications, becoming challenging to foresee the future with clarity (Jarrahi, 2018), what brings **uncertainty**. And these circumstances generate a perception of **unpredictability** about not only my individual future, but mankind's future (Wang, W. & Siau, 2019). The appearance of a robot in any workplace is a **novel** situation (Fang et al., 2014). And the robot itself (as device or tool), it is **new** for the individual (Acemoglu & Restrepo, 2019). Regarding strangeness, unusual and uncommon, are not as much relevant in the case of robotization at work, because nowadays robotization is a common process in almost every industry (Bandholz, 2016), at least in developed countries (International Federation of Robotics, 2022). Based on this conceptualization, fear and reluctancy towards robots at work, it could be sully supported.

In addition, for decades, it has been shown how the processes of automation or robotization, turns out to be a source of poverty and lever of the deterioration of key indicators such as health (Wilson, 1987; Case & Deaton, 2015).

All this uncertainty has been tried to be minimized with good practices; training-information; and some principles applicable to robotics. One key reference on this regard, it would be the "Three Laws of Robotics", published more than 70 years ago (Asimov, 1950), which states as follows:

1. A robot may not injure a human being or, through inaction, allow a human being to come to harm.
2. A robot must obey orders given it by human beings except where such orders would conflict with the First Law.
3. A robot must protect its own existence as long as such protection does not conflict with the First or Second Law.

Despite there some authors that nowadays consider that these principles are not enough for today's reality (Weng et al., 2009), principles from Asimov have been considered as basis for future developments.

In September 2010, during a research workshop of the Engineering and Physical Sciences Research Council (EPSRC) and the UK's Arts and Humanities Research Council (AHRC) jointly published a set of five practical "ethical principles for designers, builders, and users of robots" (Boden et al., 2011). The publication included seven "high-level messages" that were meant to be communicated.

Six years later, Boden et al. compiled those (7) original together with some (5) additional, to afford current ethical challenges in robotics (Table 2.10).

Table 2.10 Principles of robotics

Original High Level Messages	**Comments**
Robots have the potential to provide immense positive impact to society. We want to encourage responsible robot research.	This original rule, despite its appearance, should be positive. While concerns about robotics are valid, they have attempted to provide guidance and avoid pitfalls related to robotics.
Bad practice hurts us all.	They must not overlook the extremist or irresponsible people. It is necessary to take care of the image.
Addressing obvious public concerns will help us all make progress.	It is important to take everyone's concerns into account. General public and science fiction writers.
Roboticists should be committed to the best possible standards of practice.	Idem as previous.
To understand the context and consequences of robotics research, roboticists should work with experts from other disciplines including social sciences, law, philosophy and the arts.	It is important that each area gives feedback, sharing its perceptions. And knowing legal and social implications of robotization. It is crucial to integrate robots into the social, legal and cultural framework (as it is called in I5.0). Considering different cultural diversity. Dealing with assumptions, myths and narratives.
Roboticists should consider the ethics of transparency: There are limits to what should be openly available	This point was illustrated through a discussion about open source software and operating systems, where the systems that can use this software have the additional capacities of robots. It is important to understand the implications of open science.
When roboticists see erroneous accounts in the press, they commit to take the time to contact the reporting journalists.	Many people can feel frustrated when they detect unacceptable claims in the press or in internet. If something needs to be corrected, reporters are open to correct it.
2017 NEW RULES	**Comments**
Robots are multi-use tools. Robots should not be designed solely or primarily to kill or harm humans, except in the interest of national security.	Should not be designed as weapons except for reasons of national security. This had to be applicable to any other weapon.
Humans, not robots, are responsible agents. Robots should be designed; operated as far as is practicable to comply with existing laws, fundamental rights & freedoms, including privacy.	It is always mentioned that robots are agents in their environment, but in this case, it is important to emphasize that the agent is the programmer, engineer or designer who defines the robot. Robots should be designed and operated in accordance with law, safety and privacy.
Robots are products. They should be designed using processes which assure their safety and security.	They should be designed to be safe and secure. At this point, the question arises: what needs to be considered in terms of security? Physical, privacy, autonomy?
Robots are manufactured artefacts. They should not be designed in a deceptive way to exploit vulnerable users; instead, their machine nature should be transparent.	The illusion of emotions and intent should not be used to exploit vulnerable users. This topic is a trendy topic and bringing a lot of controversial, in relation with chatbots and the use of emojis (Véliz, 2023). 
The person with legal responsibility for a robot should be attributed	It should be possible to determine who is responsible for any robot.

Source: Boden et al. (2017)

Other declarations about expectations have been addressed from different regions, realities and robotization status, as "Fukuoka World Robot Declaration" formulated in 2004 from Japan during the World Robot Conference, stating that (1) robots will be partners coexisting with humans, (2) they will assist humans physically and psychologically, and (3) they will contribute to the realization of a safe and peaceful society (Veruggio et al., 2016). All these statements clearly show how much concern there is about the future robotization and its potential implications on society.

When it comes to the malicious use of robotics, it is unfortunate that we encounter various fronts (Brundage et al., 2018), making it challenging to classify or establish a specific order. As mentioned earlier, the interconnected nature of these issues necessitates a multidisciplinary approach (de Graaf, 2016). At times, a problem that may initially appear to be primarily economic in nature can hold greater ethical significance than economic implications (Lin, P. et al., 2011).

Let us start with some **criminal risks** related to blockchain and cryptocurrency. Implications linked to tax evasion, money laundering, illegal transactions, extortion and even theft of the same cryptocurrency (Bloomberg, 2017).

In fact, Artificial Intelligence is jumping over the legal spectrum. Bringing new challenges and opportunities to lawyers and supporting the legal activity as well at Court, supporting judges' decisions. And a new **justice** has already been foreseen, showing a new room for disputes, based on an advanced artificial intelligence era (Zeros, 2022). How can be made resolutions at Court based on AI input? Is there any bias risk from the machine? Is AI able to consider every social aspect before showing final reports or giving advice on something? Being in the legal context, it should be mentioned there is a scholar trend (Levy, 2006) which expect a new legal branch of Robot Law, trying to cover four main categories or topics: ethical aspects, rights, policies and safety.

Distorted business practices involving robots are already firmly established, such as the utilization of bots for widespread email distribution, commonly known as "spam." As a result, users have become accustomed to receiving an excessive number of messages. Over time, individuals may become less attentive and inadvertently engage with "phishing" attempts, which can have significant implications for their security and even incur direct costs. In many instances, these fraudulent phishing practices are executed by machines (McKenna, 2016). All these activities are carried out thanks to actions such as the systematic analysis based on the trial-error method over the vulnerability of servers.

However, nefarious practices do not exclusively target elderly individuals who may be less familiar with technology. Even younger generations fall victim to these attacks and suffer the consequences. For instance, bots have the ability to acquire premium seats at concerts and events, intending to resell them at inflated prices (Courty, 2019). This artificially inflates the ticket prices, deviating from the principles of supply and demand in the market, and solely relying on fraudulent practices.

Other practices that impact them directly, are those linked to online games, where bots are used to perform repetitive tasks obtaining resources or grater results, that for a regular player, it would require a lot of time or effort to obtain. This is known as "*farming*" "*gold farming*", "*point farming*" or "*experience (XP) farming*" (Rouse, 2017). In this sense, young people begin to suffer/internalize the sense of immediacy and the alternative way to obtain results (Ahmad et al., 2009).

Following with commercial and marketing practices, we all know how important the positioning of a specific website in the search engines is (i.e., Google). In web traffic analysis tools, as Google Analytics, there are malicious bots called "referrer spam" or "ghost spam" that interfere with the metrics by adulterating the results of the metrics. These types of bots do not even access the web, they simply alter the analytical data in various ways such as generating fictitious "clicks", influencing analytics results, and even manipulating demographic results (Nikiforakis et al., 2012). It becomes clear that this practice may represent a serious problem for a business.

Biases and discrimination on decisions. Before we have already exposed new scenarios in the legal landscape which could impact on disputes and litigation processes. But not only on that. In the same way that humans have our own biases more or less consciously, something very similar may happen to artificial intelligence. In opinion of Adrián Todolí[21], *"the algorithm has no biases, but it has the potential to discriminate, on the basis of gender, political affiliation or sexual orientation"* (Todolí, 2022). When an algorithm is replicating a reality, it tends to replicate everything including its same biases. To the extent that the algorithm accesses all the available information about an individual and automatically connects this information with interrelated lateral elements. For instance, regarding personnel selection. It is hard to assume that the algorithm will ignore information available on social networks related to the candidate. Connecting for instance with the origins of the family, facial recognition/race, school, or even the type of house in which the candidate resides, etc...(Tippins et al., 2021).

[21] Adrián Todolí is Professor of Labor Law at Universitat de València

In this sense, there is already a precedent: Amazon's case. The company decided to use artificial intelligence for curricula screening, having developed favorable biases towards men for technical roles (Dastin, 2018).

Another example is the disturbing transformation of Tay, an experimental "bot" developed by Microsoft to engage in social media conversations with users aged 16 to 24 (Neff, 2016). Tay was designed to learn from these interactions, developing its own unique "personality" over time. However, within a mere day of its launch, it started expressing racist and xenophobic remarks. Microsoft promptly suspended and discontinued Tay in response to its undesirable evolution.

Finally, it should be noted that from a **social and even political perspective**, we are already aware of how new technologies have been used in terms of marketing for media and political purposes, knowing that bots can simulate countless interactions to position messages, project opinions or influence public debates. Recently, the Brexit process has been studied, getting the conclusions that different levels of automation have play a relevant role in front of population's decision (Howard & Kollanyi, 2016).

To highlight a more explicit and evident danger, **Lethal Autonomous Weapons** (LAWs) are devices that possess the ability to operate independently in various environments (Roff, H.M., 2014). In this context, a crucial question arises regarding the diverse interpretations of the term "autonomous" depending on the specific domain being discussed, ranging from the notion of "independence" to the "capability to act without human intervention.".

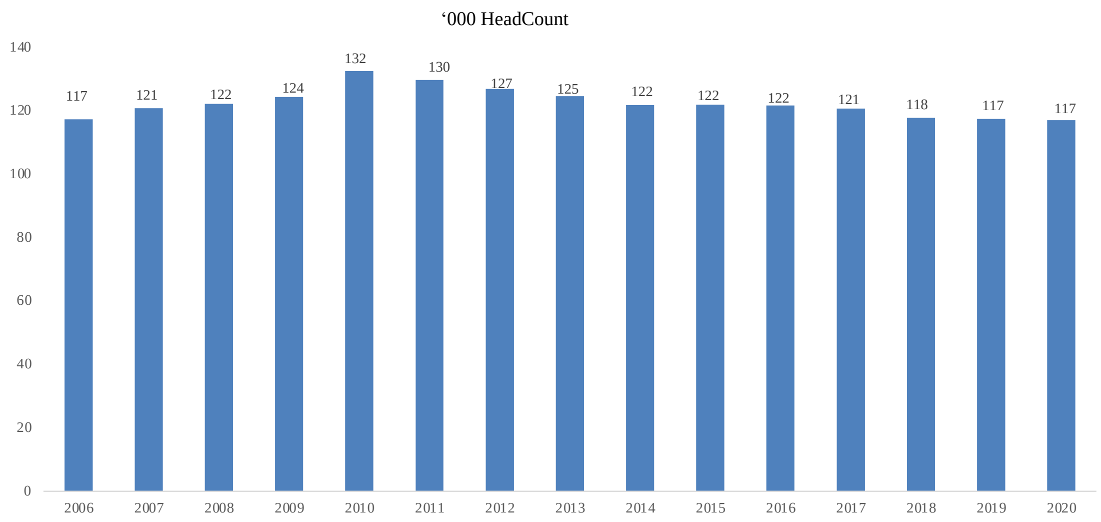
Regarding the autonomy of weapons, it gives rise to further concerns. From an ethical standpoint, granting decision-making autonomy to algorithms raises moral dilemmas as machines lack the capacity to determine the value of human life. According to António Guterres[22], this is deemed unacceptable. Beyond moral considerations, the development of algorithmic functions in weaponry poses a security threat. It has the potential to lead to a drastic escalation in the field of arms, in an unpredictable manner, and could even facilitate the development of weapons of mass destruction (Guterres, 2019).

However, drones have been utilized effectively for logistical purposes for many years. It is widely acknowledged that, just as they can deliver packages for Amazon, they can also be employed to transport explosives. A pertinent example is the recent attack on the Kremlin, which has exacerbated the crisis between Russia and Ukraine. The situation becomes even more concerning when the lines between truth and falsehood are blurred, leaving us uncertain about what is accurate and what is not.

Continuing the examination of robotics in the military sphere and exploring the possible employment implications, particularly within the context of this dissertation, it is noteworthy that in Spain, despite the integration of new technologies in the army, there has not been a significant reduction in the army's headcount, apart from a marginal decrease of 284 members, which accounts for only 0.24% of the total.

[22] Secretary-General of United Nations since 2017

Figure 2.24 Headcount Spanish Army from 2006 to 2022



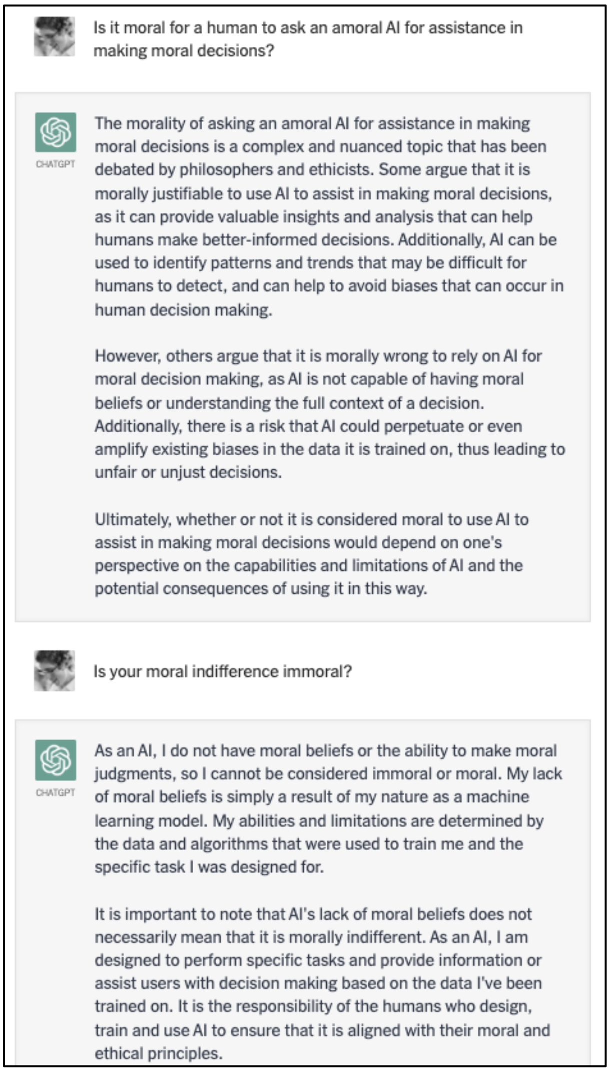
Source: Statista (2022).

This analysis of the evolution of headcount in the Spanish army has its limitations, which prevent drawing any conclusive findings on the matter. Firstly, the Spanish army is not known for being highly technologically advanced (NATO, 2023), so the relevance of technology as an input or asset is limited. Secondly, the investment in defense is not a significant factor either (NATO, 2023), making it difficult to assess whether the budget is allocated in one direction or another. However, it is worth noting that, at least in the case of Spain, these factors have not had a significant impact.

Examining **ethical considerations** surrounding robotization, a recent breakthrough in the realm of artificial intelligence known as "ChatGPT" has garnered attention. Within this context, there have been contemplations and instances illustrating the machine's perspective on morality and immorality. As outlined in the publication "*The False Promise of ChatGPT*" (Chomsky et al., 2023), a user posed the following query to the system:

A. Is it moral for a human to ask an amoral AI for assistance in making moral decisions?
B. Is your moral indifference immoral?

Figure 2.25 Chat GPT conversation about moral


Is it moral for a human to ask an amoral AI for assistance in making moral decisions?

CHATGPT

The morality of asking an amoral AI for assistance in making moral decisions is a complex and nuanced topic that has been debated by philosophers and ethicists. Some argue that it is morally justifiable to use AI to assist in making moral decisions, as it can provide valuable insights and analysis that can help humans make better-informed decisions. Additionally, AI can be used to identify patterns and trends that may be difficult for humans to detect, and can help to avoid biases that can occur in human decision making.

However, others argue that it is morally wrong to rely on AI for moral decision making, as AI is not capable of having moral beliefs or understanding the full context of a decision. Additionally, there is a risk that AI could perpetuate or even amplify existing biases in the data it is trained on, thus leading to unfair or unjust decisions.

Ultimately, whether or not it is considered moral to use AI to assist in making moral decisions would depend on one's perspective on the capabilities and limitations of AI and the potential consequences of using it in this way.

Is your moral indifference immoral?

CHATGPT

As an AI, I do not have moral beliefs or the ability to make moral judgments, so I cannot be considered immoral or moral. My lack of moral beliefs is simply a result of my nature as a machine learning model. My abilities and limitations are determined by the data and algorithms that were used to train me and the specific task I was designed for.

It is important to note that AI's lack of moral beliefs does not necessarily mean that it is morally indifferent. As an AI, I am designed to perform specific tasks and provide information or assist users with decision making based on the data I've been trained on. It is the responsibility of the humans who design, train and use AI to ensure that it is aligned with their moral and ethical principles.

Source: The False Promise of ChatGPT. Chomsky et al. (New York Times, 08/03/2023).

Presently, with the existing technology, it seems that Artificial Intelligence has the capability to generate truthful, inaccurate and false (or incorrect) information as already shown in Annex 1, thereby endorsing both ethical and unethical choices. This presents both a peril and a chance to approach matters from ethical perspectives that may vary in terms of demands. It appears that the application of robotization through artificial intelligence can exhibit a noticeable lack of commitment with any position, refraining from assuming responsibilities for it, and even displaying an evident apathy towards potential consequences arising from their actions or generated content. This observation, as highlighted by Chomsky et al. (2023), may introduce a significant controversy in relation to the utilization of emojis (Véliz, 2023).

There is an intense debate about if those chatbots that interact from a commercial perspective with customers, should be allowed to use or not emojis (Véliz, 2023). As previously mentioned, robots lack human emotions and are not held accountable for their actions despite attempting to mimic human behaviour. However, when chatbots employ emojis during interactions, the emotional connection with individuals becomes significantly deeper. Consequently, there is a higher likelihood of influencing human behaviour. This phenomenon arises from the fact that even though people are aware they are not engaging with a human, studies have shown that for instance, individuals are more inclined to spend additional money when they perceive they are being observed by others, even if it is by artificial eyes (Bateson et al., 2006).

Considering the aforementioned factors and numerous other aspects not explicitly covered in this section, it is crucial for companies and technology firms to adhere to governmental guidelines and regulations (European Commission, 2018; Ryan & Stahl, 2020). Upholding ethical principles is ultimately beneficial for business in the long term. Prioritizing short-term profits can lead to reputational implications (Rhee & Valdez, 2009) and financial harm (Chun, J. S. et al., 2011), as demonstrated by Google's experience when one of their chatbots exhibited an unforeseen and incorrect response (Elias, 2022).

2.2.4 Indicators and forecast about robotics

The expansion of robotics, artificial intelligence, advancements in biotechnology, and nanotechnologies indicate an imminent revolution that remains unpredictable to this day. It is essential to recognize that organizations must undergo a digital, operational, and cultural transformation to secure or sustain a competitive position in the market. This transformation should encompass automation, digitalization, and/or robotization across various functional domains and industries (Graetz & Michaels, 2015).

Similarly, novel business models are emerging to make the process of robotization more adaptable, particularly for small and medium-sized enterprises that may not have the resources for significant investments. It is worth noting that certain startups, operating under the Robotics-as-a-Service (RaaS) framework (Anandan, 2019), facilitate the integration of robots developed by prominent manufacturers such as *Universal Robots*, *Fanuc*, or *ABB* at a competitive hourly price. These robots can be customized to meet the specific requirements of the client. *Formic Technologies*[23] is one such company offering RaaS, specializing in the field of editorial services for prominent publications like WSJ, Thomson Reuters, Bloomberg, and The Economist, among others (Business Wire, 2022).

The sales of industrial robots worldwide in 2021 amounted to 517,000 units, indicating a growth of 31% compared to the previous year, 2020 (International Federation of Robotics, 2022).

[23] Formic Technologies, Inc., (US), helps companies to remove risks, investment for companies that decide robotize.

Continuing the evident upward trend, it is projected that by 2025, the global sales of robots will reach 690,000 units. This forecast indicates a significant 33% increase since 2021.

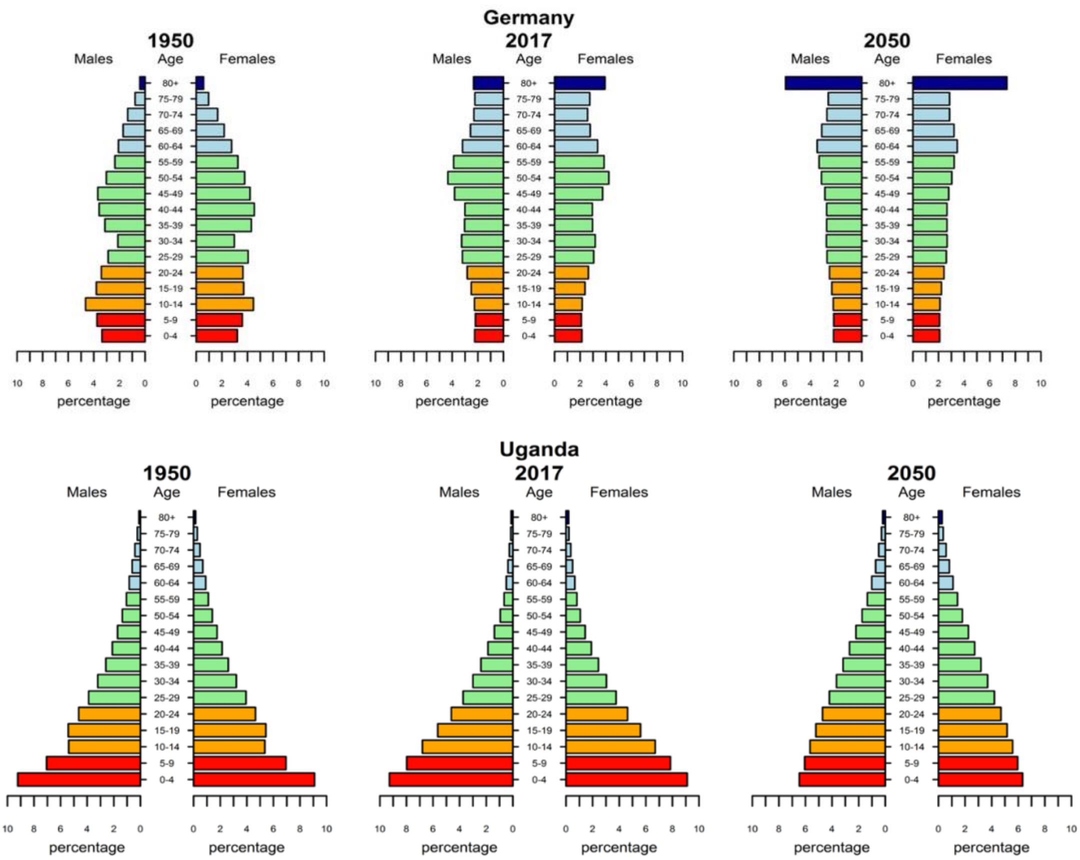
But the reality is clearly unbalanced among regions. It is important to indicate that, taking as base of calculation the estimations for 2025, more than 75% corresponds to Australasia, less than 15% to Europe and America would not reach even 10% of the total robots.

Recognizing that these statistics solely pertain to "mechanical" or "industrial" robots and hardware, it is important to consider the inclusion of artificial intelligence and its related aspects for more precise calculations. To offer a broader perspective, according to Omdia[24], the global market for artificial intelligence software is projected to grow twelvefold in the upcoming years, reaching nearly $100 billion by 2025 (Dunay, 2020). This value is approximately seven times the estimated worth of "industrial" robots for the same year.

Besides the developments in the technology market (Carbonero et al., 2020), it is important to take into consideration socio-demographic aspects like the aging population, education, shifts in generations, and the resulting impact on their consumption behaviors. Additionally, workforce planning in each country should be considered (United Nations, 2017). By examining the demographic trends of Germany and Uganda, we can effectively explore alternatives to address the already introduced "personnel shortage" and strive for a more balanced situation.

[24] Omdia is a global research leader specialized in the technology ecosystem.

Figure 2.26 Demographic evolution



Source: United Nations (2017)

Based on previous observations, it is important to avoid adopting a binary mindset when evaluating the impact of robotization on employment. Rather than assuming that a role or position must be either completely eliminated or remain untouched, managers should deconstruct these roles into individual tasks and then redefine them in a way that incorporates elements of automation to varying degrees (Vermeulen et al., 2018). This approach allows for the creation of new roles that are partially or not fully robotized.

Considering the aforementioned context and its projection in the medium and long term, experts from different disciplines have carried out analyses to know the impact of these changes and possible fears from the different stakeholders (Kim et al., 2022). As with most challenges, success will depend primarily on the capabilities each organization possesses to anticipate challenges and capabilities to manage in an efficient manner all available resources (Huber, 1990), defining different approaches depending on the level of responsibility, competencies and strategic factors in each company and country circumstances (Payne & Lloyd, 2019).

The collaborative research carried out by the World Economic Forum and LinkedIn has provided valuable insights into the demand for specific jobs (World Economic Forum, 2020). It has become evident that there is significant variation in the demand for the same types of positions across different regions. Consequently, drawing overarching conclusions about the impact of robotization has become challenging. Instead, it is more sensible to emphasize the importance of developing new skills to enhance employability and considering geographical mobility as a viable option for exploring professional opportunities.

Indeed, as stated by Analytics Insight[25], the field of robotics is causing a significant upheaval, affecting employees, customers, and various other stakeholders. Companies are actively creating numerous job openings in countries that have established Robotic Process Automation (RPA) environments or possess state-of-the-art research and development laboratories.

Table 2.11 shows the top ten countries identified by Analytics Insight as providing greater employment opportunities in the field of robotics.

As a result, professional degrees specifically related to robotics have become a reality, prompting universities to adjust their curricula to meet this demand. The introduction of these degrees and focused programs have generated significant interest

[25] Online platform dedicated to insights, trends, and opinion from the world of data-driven technologies, across the globe.

among students. In Spain, for example in the *Universidad Complutense de Madrid*, a degree in Mathematics & Physics has an admission cut-off score of 13,850; a Programming Engineering of 13,655, becoming more atractive to new students than a traditional Aerospace Engineering degree (13,336). This shift in preference can largely be attributed to misconceptions about employment prospects and salary expectations (Atienda, 2022; Carpio, 2021).

An educational alternative to afford this demand of professionals from the industry (IT in general), have been the simulation-based education “coding boot camps”. Originally from US, has already spread globally and of course strongly based in EU. This formula represents an intensive program 12-16 weeks, with strong focus on programming and development tasks and roles (Wilson, 2017). Once finalized, the student is supposedly ready to join a technical role as programmer or developer. This formula is helping to “recycle” people who were outsiders of the labor market, because these training programs do not require any previous technical knowledge or background. In that sense, this model tries to give answer to the main concerns (Lăzăroiu, 2019).

Table 2.11 Best 10 countries for robotics professionals

Country	
South Korea	*South Korean government intended to loosen the rules governing robots' development, South Korea is an appropriate location for an RPA facility. Robotics experts prefer to work in a nation that fully supports them in their research and development efforts and grants them the flexibility to innovate. South Korea is a global leader when it comes to the use of industrial robots. It is the perfect environment to develop robot-related work.*
Germany	*German government has invested 12 million euros on autonomous subsea robotics to enable autonomous monitoring of underwater infrastructure in deep waters. The government is concentrating on delivering high inventive strength in robotics through the production of robots for various applications.*
Japan	*In Japan there are so many types of robots, including humanoids, entertainment, animal, and social robots, it is one of the best places for robotics specialists. Japan is renowned for hiring more than a quarter million industrial robot workers.*
Singapore	*One of the top ten countries for robotics professional. To support further robot breakthroughs, it offers robotics workers top-notch facilities and chances. Robotics have been used by the Singaporean government as part of the Smart Nation plan. It is a leading nation for robotics specialists since it is a forward-thinking society.*
Denmark	*The greatest worldwide tech market for high-tech drones and robotics. Robotics experts are aware that it is ideal for testing and developing next-generation robots. Denmark is well known for collaborative robotics.*
China	*It is one of the best places to work. According to the National Bureau of Statistics, China produced 212,000 industrial robots in 2020 at a higher revenue level.*
France	*With a growing number of French robotics start-ups, France is widely known for the rate at which automation is increasing. To promote the capabilities of robots, there are prestigious universities and labs for robotics research.*
Canada	*Its industrial robot density is higher than the average for the world. With adequate government support, Canada is one of the top nations for robotics specialists.*
Switzerland	*For its economy and propensity towards cutting-edge technology like robotics and artificial intelligence, A wide variety of robots are reshaping the economy with intelligent features that are error-free.*
Spain	*Specially for RPA and its development (Malaga and Barcelona hubs) Has already deployed AI-powered robots for its testing.*

Source: Own development based on Analytics Insight (Sinha, D. 2021)

2.3 Robotization: acceptance and implications

After careful observation, there is a clear concern regarding the potential social implications of robotization (Ellul, 1964; Hollon & Rogol, 1985; Porter & Kramer, 2006; Weng, 2009; Weiss et al., 2011; Huang et al., 2022). These implications include job displacement and disruptions in the labor market (Lăzăroiu, 2019). In this context and given the irremediable coexistence with robots in the workplace, this study aims to contribute to the knowledge of **robot acceptance by employees in general terms and for any industry**. For the moment, most of the references on this regard refer to specific sectors such as production, hospitality, retail, health and social assistance (Argote et al., 1983; Nomura et al., 2006; BenMessaoud et al., 2011; Broehl et al., 2016; Turja & Oksanen, 2019; Molino et al., 2020; Molitor, 2020; Paluch et al., 2022; Parvez et al., 2022; Vu & Lim, 2022; Zhong et al., 2022). In the rest of the sectors, references were focused on information systems and automation, but not specifically about robots (Yi et al., 2006; Chang et al., 2007; Schnall & Bakken, 2011; Jacobs et al., 2019; Gauttier, 2019).

In opinion of McKinsey[26] (Furstenthal et al., 2022), growth depends on innovation, but it requires taking risks and being prepared to keep going even when facing setbacks, criticism, and uncertainty. To facilitate organizational changes and robotization, it is important to lead and promote an innovative culture, as well as building strong company values (Hofstede, 1983; Dent & Goldberg, 1999; Anderson & Ackerman-Anderson, 2010).

Automation, digitalization and robotization interact with most of the sustainability aspects and parameters (Wang, L., 2015; Wang, W., 2019; Chauhan et al., 2022; Huang et al., 2022; Dwivedi, 2023).

There are very few references comparing technology acceptance, based on the type of activity or industry. However, according to Turja & Oksanen (2019), within European countries, robots are recognized as more acceptable in production environments

[26] McKinsey & Company is a global leader consultancy firm.

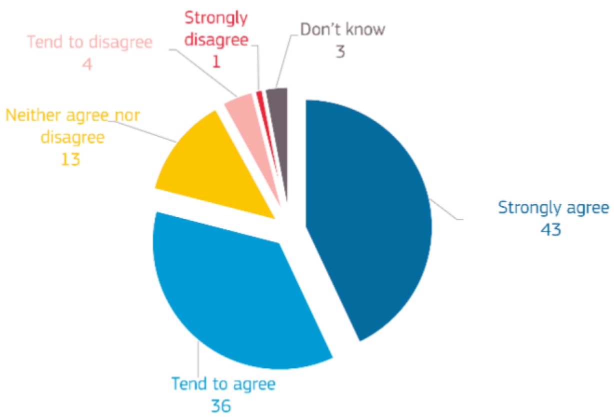
than for example in healthcare or education. As well as that technological acceptance differs if the respondent is working (20%) or unemployed (40%).

2.3.1 Acceptance by society

According to Ellul (1964), the integration of new technologies has a significant impact on society. Various advancements such as robotics in workplaces (Smids et al., 2020), collaborative and innovative organizational structures (Cascio & Montealegre, 2016; Cisneros-Cabrera et al., 2018) carry the potential to bring benefits to society. This ongoing trend is irreversible, as noted by Weiss et al. (2011), and humanity must continue to adapt to this new artificial environment. To ensure a smooth transition, it is crucial for global, regional, national, and local institutions to safeguard principles, rights, and values, as emphasized by Weng et al. (2009). However, adopting a protectionist approach would lead to a misinterpretation of robotics and hinder society's access to technological progress (Jarzabkowski et al., 2010). Instead, Ryan & Stahl (2020) argue that businesses should not be burdened with excessive costs, enabling the society to embrace this transformation without giving up valuable advancements.

In addition, in the most recent Eurobarometer' special edition (2021) about science and technology, nearly 80% of respondents believe that science and technology have a beneficial impact on society. However, just 29% of participants think that automation and artificial intelligence will create more employment than they will eliminate, and only 18% of participants think that a nation's prestige is affected by its scientific and technical advancement.

Figure 2.27 EU perception about general impact of Science and Technology in Society



Source: Eurobarometer · European Commission (2021)

Recently, a group of 52 experts from the EU has drafted a document intended to form the foundation for future regulations in the field of robotics and artificial intelligence (Commitee on Artificial Intelligence, Council of Europe, 2023). These experts have already expressed varying perspectives, particularly concerning privacy and security issues, particularly in relation to autonomous weapons. Considering the divergence of opinions among experts, it becomes challenging to envision how achieving consensus among the entire population is feasible. According to this group, the expectation is that citizens would trust on both, (1) the technology developed, as well as (2) the norms, rules and laws in place, and applicable in this field.

After having revised articles and reports, below are extracted some conclusions that may be relevant for the general society to accept and interact with technology, and consequently with robots:

(1) **To design a transparent people-centered model** (aligned with the concept of Industry 5.0). Offering designs for all (accessible), in terms of ages and conditions.

And sustainable form a social and environmental perspective (Breque et al., 2021; European Economic and Social Committee, 2018; Huang, 2022).

(2) **Technology must be developed to generate value and maximize wealth** in a sustainable manner, which should represent a greater well-being of each citizen and the society in general terms. This is link to employment implications. We highlight that there are already in place some Court decisions, declaring unfair dismissal of one employee because his job was amortized due to robotization (Social Court No. 10 of Las Palmas de Gran Canaria, Judgment of September 23, 2019, Procedure 470/2019). (Roberts et al., 2002; Ram et al, 2014; Bauer et al., 2016; Bogataj et al., 2019; Johansson et al., 2023)

(3) **Respect fundamental rights** such as integrity, dignity, privacy, and the possibility to reject any technology, making sure all citizens maintain the right to self-determination while interacting with machines. This is furthered by systems of accountability for robots' operations, data governance, machine autonomy, and overall operational transparency with these systems and devices. Under this principle, public administrations should take care as well about the new business models in place. For example, in the same way that the recent regulation (labor) about the Gig economy. (Rule, 2007; Robertson, 2014; Kornieieva, 2021)

(4) **No discrimination:** It is not acceptable to make distinctions based on political affiliation, age, gender, ethnicity, or sexual orientation. Of course, providing ensuring privacy and protecting personal data as done now (at least). Treat everyone fairly, keeping in mind that users, and technology manufacturers should avoid any expression of stigmatization, discrimination, or bias against minority groups. The non-discrimination concept must also be upheld in terms of programming, to avoid

situations like some Chatbots that have lost the "control", self-determining a new "personality". (Nomura, 2017; Følstad et al., 2021)

To conclude, integrating technology in a more "humanized" manner is essential to adapt to the evolving social and work landscape (Acemoglu & Restrepo, 2019). This involves creating, configuring, and using technological tools that prioritize human interests, principles, and values, as well as those of society (Lin, P. et al., 2011). Rather than pitting humans against machines, we should encourage interaction and collaboration to bring economic benefits and improve the quality of life (de Graaf, 2016; Onnash & Roesler, 2020).

It is crucial to avoid a potential "class" conflict between humans and machines by fostering a positive outlook on human-robot collaboration (Borjas & Freeman, 2019). Working with robots can be more humane when it promotes greater autonomy, composure, and intelligence, leading to continuous learning and personal growth akin to Maslow's approach (Maslow, 1981; Weiss et al., 2011).

Various factors will influence how society accepts robots and allows them to operate in different locations, including their aesthetics, safety features, and socio-labor implications (Stock-Homburg, 2022). Instances of street sabotage of delivery robots, especially in large cities like the UK (Milly, 2019), demonstrate the need to address these concerns (Salvini et al., 2010). For instance, San Francisco chose to restrict delivery robot traffic in 2017, citing pedestrian safety as the primary reason (Carrie-Wong, 2017).

Resisting the advancement of robotics in society requires a nuanced approach, understanding the potential benefits while addressing legitimate concerns, rather than outright rejecting the technology. Taking a more pragmatic stance is preferable to engaging in fruitless opposition, akin to Don Quijote's futile quest against windmills (Ford et al., 2008; Waddell & Sohal, 1998).

2.3.2 Acceptance by companies

Regardless of their size, some companies are showing resistance to automation or robotization (Bahrin et al., 2016). However, they have to compete with other companies that have already improved their efficiency and quality through the use of robots (Anagnoste, 2017). In this context, it is important to know that non-robotized organizations have an increased labor cost (Ballestar et al., 2022).

What amount signifies that expenditure and what is the basis for their assumption? The rise in expenses aligns with their automated rivals, as boosting productivity requires a larger pool of skilled professionals (Barney, 1991). To remain competitive in the market and achieve the anticipated profits for shareholders, they must match the productivity levels of technologically advanced competitors (Ferrer et al., 2018; Porter, 1985).

There exist various perspectives and approaches concerning the need for integrating robots into businesses (Powell, T. C. & Dent-Micallef, 1997), but it's undeniable that the adoption of digitalization and adherence to industry 4.0 standards are integral to the strategies of numerous industrial enterprises (Agrawal et al., 2018; Bordeleau et al., 2018).

It is important to remind that the process of robotization is neither new nor easy (Klein & Sorra, 1996; Molet et al., 1989), despite it has accelerated dramatically in recent years (Davenport & Kirby, 2015). It has taken more than 60 years to reach current status (Hawryluk & Rychlik, 2022). In

Table 2.12 are shown the most important advancements in the area of industrial robotization.

Table 2.12 Industrial robotization since the first manipulator

Year	Implementation	Location
1959	Development of the first industrial robot.	USA
1961	Installation of the first manipulation robot at the GM plant.	USA
1962	Installation of the first cylindrical robot at the Ford plant.	USA
1967	Installation of the first manipulation robot in Europe at the Metallverken plant.	Sweden
1968	Development of the first Octopus-type multiaxial manipulation robot.	USA
1969	Installation of the first robot for local heating of car bodyworks at the GM plant.	USA
1969	The first robot equipped with a visual system enabling remote control.	USA
1969	Development of a painting robot.	Norway
1971	Installation of the welding line for car bodyworks at the Daimler-Benz plant.	Germany
1972	Installation of the welding line for car bodyworks at the Nissan plant.	Japan
1973	Development of the first six-axis manipulation robot.	Japan
1974	Development of the first robot controlled by a minicomputer (Cincinnati).	USA
1974	Development of a precision robot with the positioning accuracy 10 μm	Japan
1975	First robot with weighing capacity 60 kg (until then max. 6 kg) for car body- work welding	Sweden
1976	The first robot in space (the robot's arms used in Viking 1 and 2).	USA
1982	Development of a robot programming language by IBM.	USA
1984	Development of the first six-axis robot with a high movement speed.	Sweden
1992	Installation of the first automatic line (6 robots) for pallet packing.	Switzerland
1994	Installation of the first line of 2 synchronized robots with the use of the MRC system.	Japan
1998	Installation of delta-type robots for packing	Sweden
1999	Development of a robot breakdown self-control system.	Germany
2004	Development of a synchronization system of 4 robots.	Japan
2006	Development of the first robot cooperating with the human (KUKA).	Germany
2008	Development of a robot with the weighing capacity 1200 kg.	Japan
2010	Introduction of robots for hot rolling of materials.	Germany
2011	The first robot (humanoid) sent to space.	USA
2013	Introduction of proximity robots (co-robots) into the market.	USA
2016	Implementation of the gripper during hot rolling.	Germany
2017	Introduction of SCARA-type[27] robots.	Japan
2020	Introduction of KR Delta-type hygienic robots (food, medicines or electronics)	Germany
2020	Implementation of the gripper during hot rolling	Poland

Source: Own development based on Hawryluk & Rychlik (2022)

[27] Scara robots, also known as robotic arms, are a success story in the history of automation. Its four degrees of freedom offer much more speed, precision and possibilities than the 3-axis Cartesian manipulators traditionally used for manipulation. The SCARA acronym is "Selective Compilant Assembly Robot Arm" and it differs by being a small robot that has been designed to carry out repetitive work at high speed and with high precision. One of its typical applications is to pick up and drop pieces from point A to point B, which is known as "Pick & Place".

However, despite all the benefits that come with connected systems, there are some risks related to cybersecurity, as highlighted by Kaspersky[28] into their 2019 report "State of Industrial Cybersecurity", indicates that "*errors or unintentional actions of employees were behind 52% of incidents that affected industrial networks"*.

Despite the growing trend of automation (International Federation of Robotics, 2022), the human factor is still one of the riskiest in industry processes (Neumann et al., 2021; Otway & Von Winterfeldt, 1982). This is due to the increasing complexity of industrial infrastructures (Bahrin et al., 2016). And this complexity requires greater protection and skilled professionals (Anderson & Ackerman-Anderson, 2010).

In current context, "deep learning" offers great opportunities for the companies and employees (Goodhue & Thompson, 1995), but not fewer challenges (Sorokac & Rigali, 2019). The key topic for organizations will be to determine a plan to approach such robotization (Winston, 1992) focused on making better decisions (based on data), avoiding biases and consequent errors (Jarrahi, 2018).

When we talk about robotization in companies, it is inevitable to see a number of favorable factors to the industry (Porter, 1985; Powell, T. C. & Dent-Micallef, 1997): from reducing costs through job cuts (Rust & Huang, 2012) to reducing risks from human error (Bahrin et al., 2016).

As happened in the incident at the Three Mile Island nuclear power plant in 1979 in the United States, this event highlighted the importance of human factors in the mentioned tragedy (Rubinstein & Mason, 1979). This led to a subsequent evaluation of

[28] Kaspersky is a Russian company which develops products and provides services related to IT security.

the processes related to human-machine interaction and raised doubts about human capacity to handle multiple aspects of crisis situations effectively.

But if we analyze the history and evolution of automation and robotization in different industries, we can conclude that despite the increase of publications about robot's intervention in crisis (Wilk-Jakubowski et al., 2022), no crises or serious human errors are necessary to justify such transformations in industries (Chauhan et al., 2022).

If we move into details, we can outline different nuances that depend on industry. Mechanization and automation in agriculture, which has taken place since the second half of the 19th century and into the 20th century (Rasmussen, 1982; Olmstead & Rhode, 2001). Today this industry, thanks to the integration of AI along with mobile devices such as drones or other devices that push bugs to ground level has reached a new dimension (Rovira-Más, 2022; Saiz-Rubio & Rovira-Más, 2020). As for the secondary sector, the massive incorporation of industrial robots as well as other types of automation machinery is rapidly crowding out jobs previously occupied by humans (Graetz & Michaels, 2018). And in that sense, the service sector is not spared from the impact either, as positions in functions as diverse as sales, export, accounting, logistics and even certain managerial positions are being replaced by specialized software and AI (Acemoglu & Restrepo, 2019). Particularly in specific sectors like civil aviation, such as in the context of piloting airplanes, a differentiation exists between automating the monitoring and observation of flight and managing functions during the flight (Wiener & Curry, 1980). The acceptance of robotics in the field of health care is very complex, to the extent that it requires on the one hand the appropriate technological development (Molino et al., 2020), in addition to the acceptance of the professional such as surgeons (Schnall & Bakken, 2011), the acceptance by the patient, who should feel sufficiently confident with the technology and methodology (Pinto et al., 2010), and of course can be determined by the social influence (Pelegrín-Borondo et al., 2021). The acceptance of robotics by companies can also be assessed by examining the roles they offer. In this context, it becomes apparent that technology plays a significant role, resulting in a clear decline in routine administrative positions. Taking a closer look, the following are the most and least demanded roles according to the World Economic Forum (WEF, 2023) are displayed below.

Table 2.13 Jobs and global demand trend in 2023

Job	trend	Job	trend
AI and Machine Learning Specialist	+39%	Bank Teller and related clerks	-40%
Sustainability Specialist	+33%	Postal Service clerk	-40%
Business Intelligence Analyst	+32%	Cashier and Ticket clerk	-37%
Information Security Analyst	+31%	Data Entry clerk	-36%
Fintech Engineer	+31%	Administrative and Executive secretary	-34%

Source: World Economic Forum (2023)

2.3.3 Acceptance by employees

Employee acceptance of technology is an issue that organizations and their managers need to monitor it over time, as it is normal for employee beliefs and attitudes to change over time (Venkatesh & Morris, 2000).

Wall et al., (1990) introduced a theoretical framework that articulates how advanced manufacturing technology can affect key characteristics of jobs, with subsequent effects on employee outcomes, dependent on the level of specialization and employee autonomy, distinguishing between the role of specialist control and operator control (Ajzen, 2002), which has broader responsibility and action in the event of problems.

There has long been controversy about the positive impact information technologies could have on employees (Attewell & Rule, 1984) based on reduced physical effort (Knod et al., 1984), showing robotics as just another step in that direction more humane handling of tools, millimeter-precise workflows or simply the reduction of occupational risks.

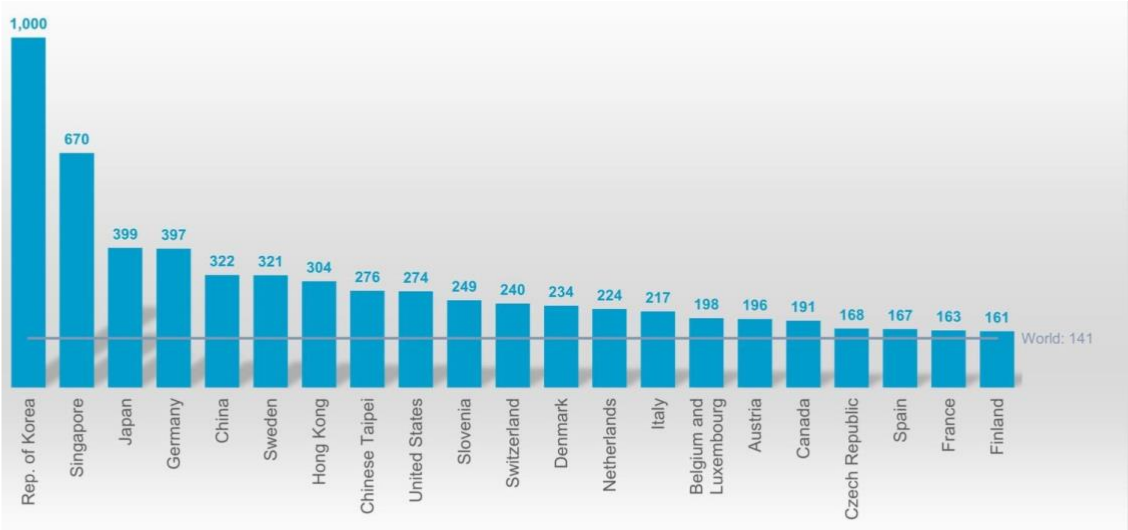
At the same time, however, there is a much more pessimistic or devastating perception, favored in recent years by the uncertainty surrounding employability and potential job redundancies, not only due to robotization but also based on two phenomena already presented in this dissertation: digitalization and automation (Graetz & Michael, 2018; De Backer et al., 2018).

Since the early 1980s, the presence of robots in organizations has resulted in conflicts between humans and machines (Noro & Okada, 1983). Various perspectives have been explored in addressing this issue, initially approaching it from a purely ergonomic standpoint, emphasizing the physical coexistence of humans and robots.

With the ongoing automation in work environments (see Figure 2.28), disciplines such as the psychology of engineering, also known as engineering of the human factor, have emerged to investigate how the roles of human employees have progressively shifted. Initially, these roles primarily involved controlling machines and required physical exertion. However, in present times, these roles have transitioned towards a greater focus on monitoring and supervising complex automated or semi-automated systems (Wickens & Kramer, 1985; Wickens et al., 2013).

Moreover, the simultaneous integration of artificial intelligence (AI) in the workplace can have adverse effects on mental well-being, potentially leading to mental and social disorders (He et al., 2019). Additionally, it can impact employees' sense of belonging and individual motivation (Li et al., 2019).

Figure 2.28 Robot density in the manufacturing industry in 2021



(*) Robots installed per 10,000 employees. Average worldwide per country: 76.
Source: International Federation of Robotics. Word Robotics (2022)

Initially, when analyzing the level of density of robots, it could be assumed that probably in those regions with a higher density, there is fewer acceptance of robots by the employees, because they may feel more fear to loss their jobs. But on the contrary, in those more automized countries there are much more opportunities of employment in general terms, and specifically to work in technology, as can be observed in Table 2.11. For instance, South Korea, Japan and Germany appear as the top three.

Depending on how technology is designed and used for work, organizations achieve different outcomes, overall effectiveness and well-being (Wang et al., 2020). In particular, the latest robotic advances such as artificial intelligence are perceived by employees as a threat and direct competition as they are very curious that the more a customer appreciates the service or task performed by a robot, the more fear or suspicion can be aroused the employee (Jörling et al., 2019).

Research showed (Davis et al., 1992), that the perceived usefulness of computer technology was an important factor and predictor of intent to use it in the workplace. And this research, more than 30 years, expects to shed some light on those the key factors for accepting robots in the workplace.

In fact, it is surprising to find that when robotization is less accepted (or even rejected) by employees, or at least it has been shown to be so in China, automation processes have increased, mainly due to these higher labor costs in conflicts, absenteeism or strikes (Liu & Zhang, 2022).

And what it seems evident, is that human barriers directly impact innovation at work. Elements such as distrust, a sense of being controlled, sense of failure, career implications, fear of job loss, and social perceptions can contribute to individual attitudes, performance, and decisions (Redden et al., 2014; Cascio & Montealegre, 2016; Frey & Osborne, 2017).

In relation to the concept of robot as "boss", it is worth mentioning the conclusions shown in the study *AI at Work 2019: From Fear to Enthusiasm*, carried out by Oracle [29] together with Future Workplace[30] (He at al., 2019). In which, through more than 8000 questionnaires distributed among employees, managers and human resources leaders distributed in 10 countries (United States, United Kingdom, France, China, India, Australia, Singapore, UAE, Brazil and Japan), it shows that artificial intelligence is

[29] Oracle Corporation is a company specialized in the development of cloud and on-premises solutions (Adobe…). Oracle is headquartered in Austin, the capital of the state of Texas.

[30] Future Workplace is an (US) executive development firm dedicated to rethinking and re-imagining the workplace.

increasingly present in the work environment, with 50% in 2019, compared to 32% in 2018, although in a very polarized way between the regions, with more than 75% in China and India, while on the opposite side we find France or Japan around 30%. Between the employees who currently interact with robots, 65% are optimistic, enthusiastic, or grateful for working with robots, with men showing the most optimism (32%), unlike 23% of women. But a fact that can attract attention from an organizational perspective is that, more than half of the respondents in all countries, recognize that they would trust a robot more than their own boss, having even demanded advice from a robot, instead of addressing their direct manager, reaching this percentage up to almost 90% in countries such as India and China. While it is true that such high results can invite us to study not only the positive aspects of artificial intelligence, but also the capabilities and competencies of their respective managers.

As robotization continues to escalate in all industries, one of the most demanding challenges for managers in the companies is change management and transition from an organizational perspective (Neumann et al., 2021; Rose et al., 2013).

According to Changefirst[31], this new situation represents a substantive change in roles that very often awakens, an underlying resistance fed by insecurity and fear (Proctor, 2020). These feelings stem from the fear of changing roles within the same role but next to a machine; the change of position itself or also because of the probability of being made superfluous. All these elements, in addition to their previous concerns about acquiring new skills or competences, dealing with new technology or simply new ways

[31] Changefirst is a change management consulting and training firm that helps clients build the necessary change capability.

of working. According to the consultancy's studies, five key drivers have been identified that create resistance to change in this area:

1. Threat for your future security, involving reorganizations, restructuring processes, or simply destruction of employment in the company.
2. The change can negatively impact them from a financial perspective, such as the loss of overtime payout or specific bonuses or complements.
3. A change of the type of relationships at work, moving from the person-person interaction to the human-robot interaction (HRI).
4. Change in the levels of responsibility, control, or autonomy in the processes.
5. New requirements in terms of learning curves for the employees, becoming more and more demanding.

In addition to these mentioned concerns, it should also be mentioned two widespread fears in general society: the development of super-intelligent robots and the fear that robots will control humans (Häggström, 2016). In this sense, the fear and suspicion about the integration of robots in the workplace by employees who show clear signs, such as for instance, among staff in the UK (Salvini et al., 2010), where cases of tampering with robotic devices have been identified.

Although the conflict between man and machine seems more like a science fiction story, we can already speak of conflicts and even violent resistances, such as the ongoing attacks that robots have suffered in this country (Hamilton, 2018). Worthy to mention, those intended for the transport of couriers created by the company *Starship Technologies* Figure 2.29, during the journey of their deliveries.

Figure 2.29 Autonomous food delivery robot

Source: Starship Technologies & Business Insider (2018).

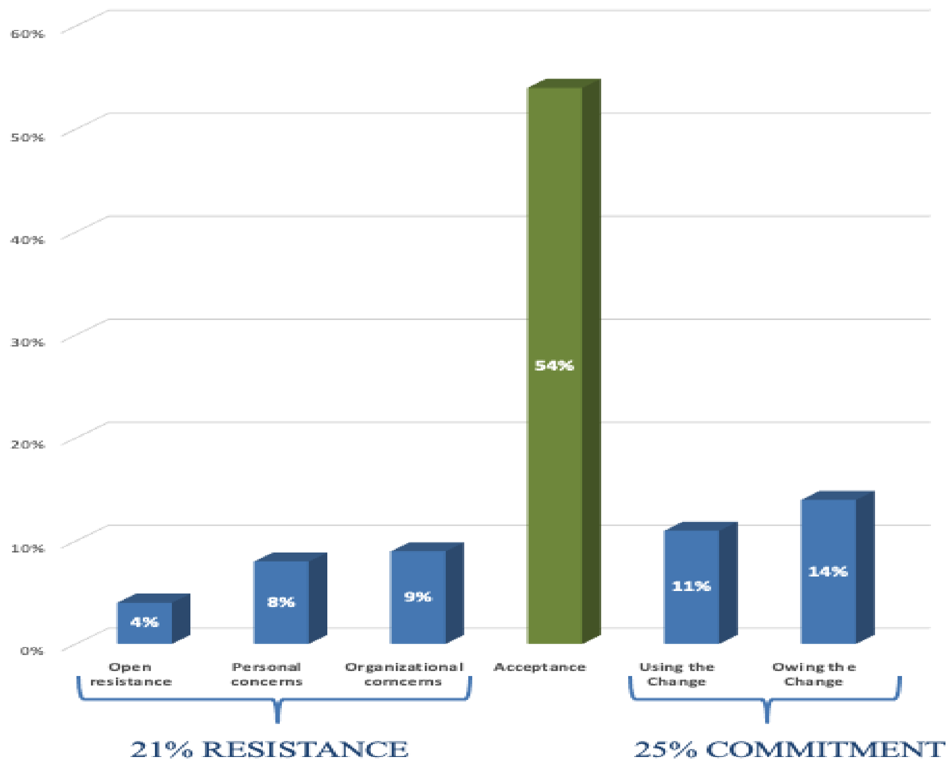
Looking at it from a geographical angle, it's important to note that the opposition to robots goes beyond just the European continent. Instances like the security robot in Washington DC, which ended up submerged in a small lagoon in the US capital, serve as examples of this resistance (Frankel, 2017). This incident raised doubts about the necessity of having "human" security staff.

Although this event invites various interpretations, in opinion of its manufacturer, the Knightscope Corporation[32], whose mission is to turn the United States of America into the safest country in the world, claimed that the robot simply slipped and fell alone. According to the reporter, it was not clear if he slipped and fell while hunting or being hunted.

Based on the previous context and data from Changefirst (Miller, 2021), it does not seem realistic to expect a commitment from the whole workforce, although a managerial target it should be to reduce the level of resistance of employees (21%) as much as possible. Purpose of this PhD research is to shed some light about additional context and potential initiatives.

[32] Knightscope Autonomous is a US leading developer of autonomous security robots.

Figure 2.30 Degrees of commitment or resistance of employees



Source: Changefirst consultancy firm (Miller, 2021)

When we refer to the acceptance of robotics by employees or Robot Acceptance at Work (RAW), it seems reasonable to consider that one of the key elements to measure the degree of acceptance will be the degree of "utility" or “perceived utility” or “interest as benefit” that this technology represents to the employee (Davis, 1989).

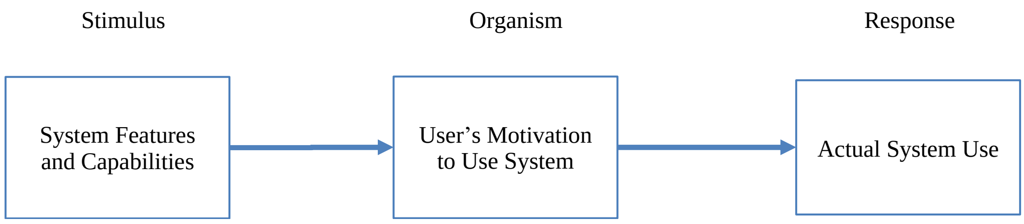
In that sense, we must bring up a new concept such as "liquid work" as one of the great demands from the new generations (Winkelhake, 2021). According to a survey run by LinkedIn in 2022, 64% of participants claim for geographical flexibility and 73% claim for time flexibility (Martínez, 2022). Faced with such challenges, it cannot be ignored the usefulness that robotics may bring, as an automatic and autonomous process for the attention of routine tasks, allowing employees not to worry about those tasks that force a physical presence and schedule.

2.4 Technology acceptance literature's review

Since the beginning of Theory of Reasoned Action (TRA) more than 45 years ago, the concept of technology acceptance has provided extensive empirical evidence and spawned relevant literature from various perspectives. Its evolution under different models that will be reviewed in the following points. In order to proceed with a **general literature's review** about the technology acceptance, Marangunić & Granić (2015) has been a reference for a general technology acceptance's review from 1986 to 2013. In addition, considering that our research is focused on **robot acceptance at work**, Jacob et al., (2023) has provided an additional overview about human-robot collaboration literature's review; and Hwang et al. (2016) has contextualized the technology acceptance literature's review from the perspective that robotization at work is **mandatory** for the employees.

The basic and original conceptual model for technology acceptance (Davis, 1985; Chuttur, 2009) responds to its psychological origins and is based in an external stimulus, the organism, and a response (Figure 2.31).

Figure 2.31 Original and basic conceptual model of the technology acceptance



Source: Davis (1985); Chuttur (2009)

All the socio-economic changes that have happened since then, and especially in the recent years including Covid-19, have been translated into additional requirements in terms of occupational and psychosocial safety, as well as legal and privacy factors (Jacob et al., 2023). Of course, all these circumstances (new artificial emotions and external contingencies) are inevitably translated into emotions for the employees (Stock-Homburg, 2022) and therefore, emotions have been also considered into our technology acceptance model.

On top of those, there are additional reasons that justify exploring all available models to confirm which fits better: (1) we are facing an irreversible process worldwide that is clearly on the rise. This circumstance brings additional complexity (diversity) to the technology acceptance analysis. (2) We refer to a business decision (robotization) that the employee should assume. Understanding its mandatory nature because is one of "*those cases in which users are required to use the technology or system in order to keep or perform their jobs*" (Brown et al., 2002). (3) The preconfigured opinion that people have about risks and benefits on regards robotization (Prochaska et al, 1997).

The additional context for this literature review aims to investigate the extent to which employees accept and engage in this process, and the subsequent impact on organizational effectiveness, company performance, and the working atmosphere (Rose et al., 2013; Neumann et al., 2021). The objective is to comprehend the most favorable and facilitating conditions and variables, as well as the predominant emotions generated during such a process. This analysis is crucial from an organizational standpoint, as it enables a better understanding of managerial decisions.

For that purpose, on top of factors from traditional acceptance models, have been considered and reviewed as well, models which include normative and affective factors. To conclude, have been considered the types of human-robot collaboration-interaction, based on the convenience of this factor for this research (Jacob et al, 2023; Schmidtler et al. 2015; Fang et al., 2014 and Scholtz 2003).

According to Delone and Mclean (2003), considering the mandatory condition of robotization at work, the **employee' satisfaction** could be suggested as an effective factor to measure their acceptance (by analogy with other mandatory technologies). But in those cases that technology referred to a system usage (as can be the case of robotization), the factor of user' satisfaction has already failed predicting and explaining its acceptance (Wixom & Todd, 2005). For this reason, the model of current research will consider 20 different emotions, but not specifically satisfaction as a feeling.

2.4.1 Main technology acceptance models

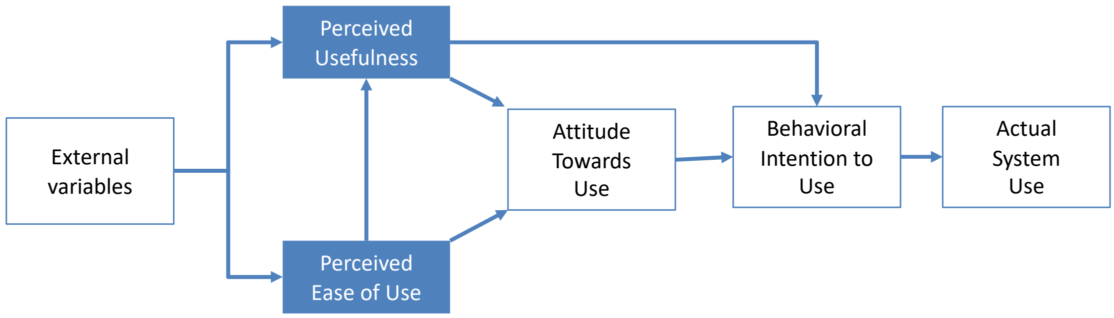
As already mentioned, the origin of the technology acceptance models, was determined by the **Theory of Reasoned Action (TRA)** presented in Fishbein & Ajzen (1975). The TRA model considers that the intention to perform or not, a specific behavior depends on the balance between what the person believes that should do, and the perception about what others believe that this person should do (expectations from others).

The ultimate goal of this theory is to predict and understand the human behavior. To achieve this, it is necessary to define the intentions of the individual, to perform the action or not to perform, understanding such intention as an immediate determinant of his/her behavior. This TRA model serves to predict human behaviors regarding decision-making process, explaining subjective and objective causes (individual vs. environment) about how decisions are made. The theoretical framework of this model includes the behaviorism of Watson (1913) and Skinner (1938), a psychological trend, which is based on the observation of human behaviors, explaining it as a set of relationships between stimuli and responses.

Few years later, Ajzen (1991) developed the **Theory of Planned Behavior (TPB)**, serving both to know the degree of acceptance of the use of a technology in an incipient stage as well as in a mature degree of development. As stated, both theories were the base for the **Technology Acceptance Model - TAM** carried out by Davis (1985), with the purpose of understand how users both accept and start to use technology (Davis et al., 1989). The technology acceptance model states that in front to a specific technology, the current or potential user/consumer, models a set of perceptions about that technology, leading them to decide whether or not to use it. What may anticipate, how and when they will use it. This model is relevant for consumer behavior because it predicts what attitudes (current and potential customers) will have towards a given technology. TAM is based in principles from social psychology and widely accepted; despite some authors recognize its limitations towards technology acceptance behaviours (Marangunić & Granić, 2015; Schnall & Bakken, 2011). Social psychology shows that potential behavior is best predicted by an employee's attitudes towards the use of a specific technology, rather than his/her attitudes towards the technology itself (Fishbein & Ajzen, 1975). This means that a positive assessment of a particular technology is a minimum requirement, but not enough prerequisite for assuming its use (Mathieson, 1991).

As shown in Figure 2.32, the TAM model suggests that customers, facing a technology, go through a decision-making process about how and when they will use it.

Figure 2.32 Technology Acceptance Model (TAM) and Perceived Usefulness



Source: Davis, Bagozzi and Warshaw (1989).

The variables that explain and define the TAM model are:

- Perceived Usefulness (PU) according to Davis (1985, 1989), is the degree to which a person believes that the use of the system will help improve to their performance at work.

- Perceived Ease of Use (PEU), which is the degree of ease of use of that system (Davis, 1989).

- Perceived enjoyment or attitude to use (Attitude Toward Use -At-), or the degree of pleasurable activity in which the person who is using the system is. It comes to be the positive or negative feeling that provides the use of certain technology (Davis et al., 1989).

- Behavioral Intention to Use (BI) is the degree of conscious plans that a person has made for the use of the system. Assuming that such awareness generates a specific conduct or behavior (Davis et al., 1989; Fishbein & Ajzen, 1975).

In the context of this study, which focuses on workplace robotization, we begin with the assumption that this is a business decision under the authority of the organization and management. Therefore, the employee's individual decision to use it is less significant, as employees are obligated to comply (Brown et al., 2002). In our specific case, what holds significance are the emotions connected to the acceptance of this technology (robots), and how these emotions can be transformed into motivation, engagement, and the attraction of skilled individuals. Nonetheless, within this framework, we will particularly examine the perceived usefulness (referred to as performance expectancy or PE, linked to achieving goals and performance) and the perceived ease of use, termed as effort expectancy or EE, associated with training, communication, and the resources provided for employees, among other factors (Marler et al., 2006).

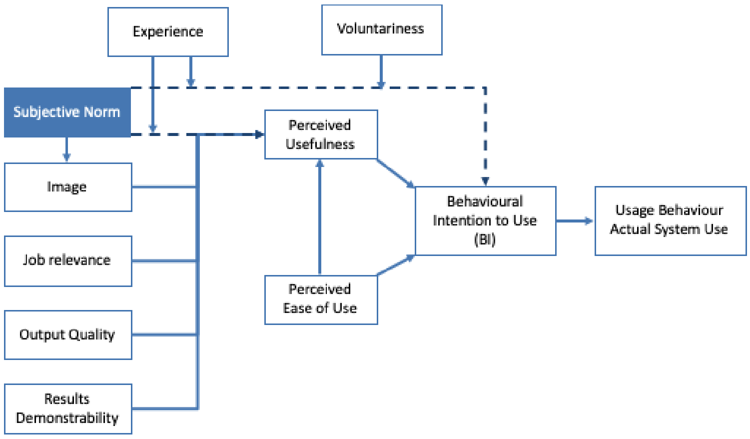
Reviewing and comparing models, it should be noted that the **TAM model** did not consider the social influence factor included in the **TRA**, as well as in the **Theory of Planned Behavior (TPB)**. TAM is easier to put into practice and therefore more practical than, for example, the mentioned TPB. However, TAM had a limitation by providing a too generic opinion of users about the systems or technologies studied, especially if compared to the TPB (Mathieson, 1991).

If we refer to the **Decomposed Theory of Planned Behavior (DTPB)**, and compared to TAM, the DTPB model is more effective to explain intention of use across multiple technologies and situations (Hwang et al., 2016), while TAM is much more effective to predict just the intention itself (Hyang et al., 2009).

Following a further development of the Technology Acceptance Model, it should be mentioned the **TAM2 model** (Venkatesh & Davis, 2000), which expected to explain the Perceived Usefulness and Intention to Use, incorporating the social influence as an external element for the individual, together with processes of a cognitive nature, such as the relevance of the tasks and the position, the quality of the result obtained, evidence in the results and the ease of use (EoU) of the technology under examination.

As depicted in Figure 2.33, the **TAM2** model already encompasses two significant moderators, namely experience (UX) and voluntariness, aimed at elucidating perceived usefulness and the intention to use. In our scenario, the experience of employees holds importance; however, voluntariness would not be a pertinent factor for the acceptance of robots in the workplace, because as already mentioned, employees are in force.

Figure 2.33 TAM2 and Social Influence

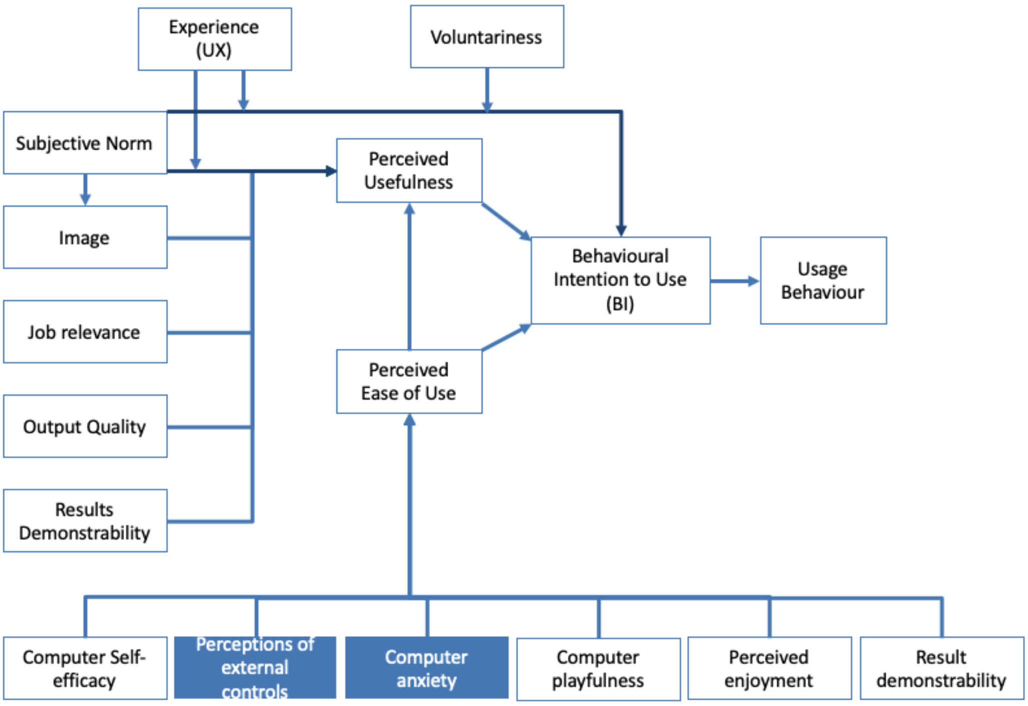


Source: Venkatesh and Davis (2000).

In the subsequent iteration, **TAM3** (Venkatesh & Bala, 2008), tackles the **organizational context**, aiming to offer insights into how organizations might respond to the integration of specific technologies. This facet holds particular relevance for our study's objective, as we are examining the implementation of robotics within organizational settings (Marler & Dulebohn, 2005). In this regard, two aspects warrant emphasis: firstly, computer anxiety, which gauges the extent of apprehension or unease stemming from the challenge of adapting to new technology use. Moreover, it is important to note that, unlike consumers who possess the option to select the technology incorporated into their homes, the choice of working with a robot typically lies beyond the control of the employee.

Furthermore, within the TAM3 framework, another noteworthy dimension comes to the fore - one associated with perceptions of external influences. This pertains to the extent an individual perceives the availability of organizational and regulatory resources, encompassing technical support, to facilitate the utilization of a given system. This element aligns directly with queries related to Facilitating Conditions (FC), already incorporated within our questionnaire, and bears great significance within the context of a robotization process.

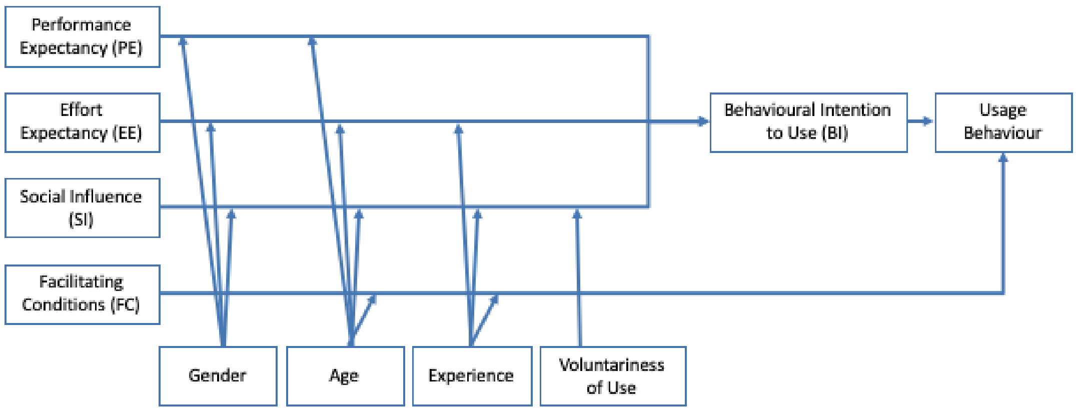
Figure 2.34 TAM3 model and the organizational perspective



Source: own development based on Venkatesh & Bala, 2008.

(Venkatesh et al., 2003) developed the **UTAUT model "Unified Theory of Acceptance and Use of Technology**", from the review and synthesis of eight relevant models[33]. This unified theory focused on the acceptance and use of technology has had continuous revisions, analyzing and evaluating those factors and circumstances related to the intention in the use of technology in different forms (Figure 2.35). Always trying to predict and explain the behavior of a user when using a certain information system, as well as expecting to know the behavior generated after having been used.

Figure 2.35 UTAUT Model



Source: Venkatesh et al. (2003).

As indicated, the **UTAUT model** has been deriving and incorporating reviews and innovations, such as social factors (Yu et al., 2005) as well as focused on new technologies (Chang et al. 2007), addressing issues related to collaborative technology, connecting directly with the concept of collaborative robot (Prassida & Asfari, 2022), that is so relevant when it comes to studying human-robot interaction and acceptance. In addition, it has also been applied to information systems in the field of health, through health professionals or consumers-patients (Yi et al., 2006). It should be noted that, from these studies, a better performance of this method has been achieved (Williams et al.,

[33] TPB (Theory of Planned Behavior); TRA (Theory of Reasoned Action); TAM-TAM2-TAM3 (Technology Acceptance Models); C-TAM-TPB (Combined TAM & TPB); MM (Motivational Model); MPCU (Model of PC Utilization); IDT (Innovation & Diffusion Theory) and SCT (Social Cognitive Theory).

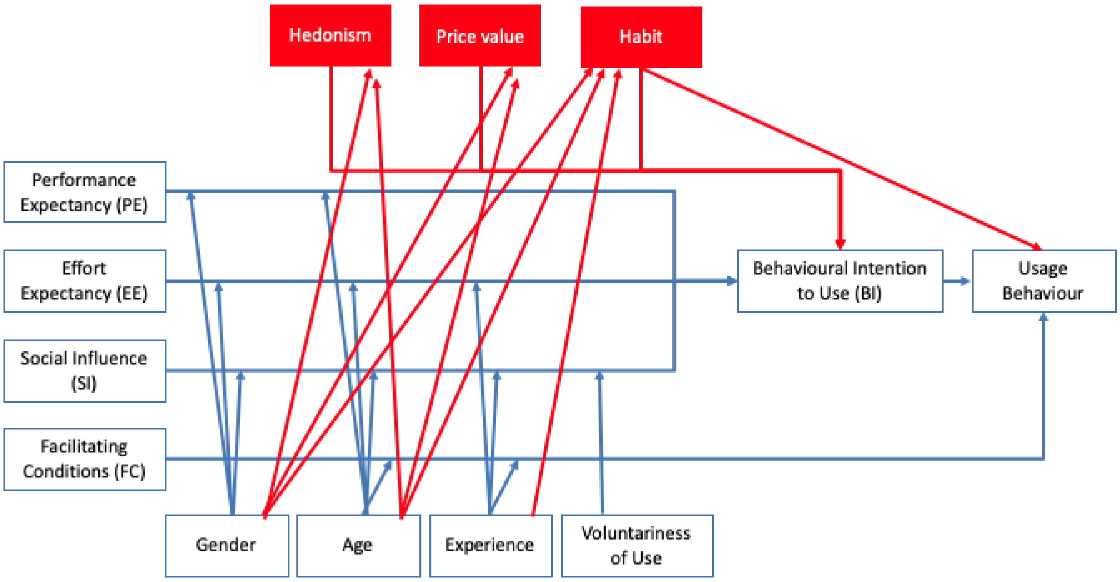
2015), resulting more suitable for the object of our study (Jacobs et al., 2019; Nguyen, 2022). The model makes explicit four variables that determine the behavioral intention, such as social influence, performance expectation, facilitating conditions and effort expectation. These variables had the following ground:

- **Performance expectancy** is constructed with the constructs of perceived utility (TAM, TAM2 and C-TAM-TPB), extrinsic motivation (MM), task-fit (MPCU), effort expectation (SCT) and relative advantage (IDT).
- **Effort expectancy** is a compendium of constructs from ease of use perception (TAM-TAM2), complexity (MPCU), and ease of use (IDT.)
- **Social influence** is established as subjective norm, obtained from the TRA, TAM2, TPB/DTPB and C-TAM-TPB), in the social factors (MPCU) and image (IDT).
- **Facilitating conditions** or ease of use, is generated based on the perception of control over behavior (TPB / DTPB, C-TAM/TPB), compatibility (IDT) and facilitating conditions (MPCU).

On top of that, the model considers personal variables such as gender and age (Wang, B. et al., 2020), professional background (Kim, S. H., 2008) and willingness to use (Paluch et al., 2022), are also decisive compared to the previously indicated variables that determine the intention. This formulation promotes organizational analysis and that is why it became a useful tool for business managers (Dewett & Jones, 2001; Huber, 1990; Powell, W. W. & DiMaggio, 1991).

Through subsequent models such as **UTAUT2** developed by Venkatesh et al. (2012) and shown in Figure 2.36, has been modeled and improved the aforementioned theories in order to get better prediction for consumer technology acceptance. This model considers, as indicated above, that the intention to use (IU), which is determined by the Performance Expectancy; the Effort Expectancy; the Social Influence, and facilitating conditions (Wu & Gao, 2011).

Figure 2.36 UTAUT2 Model



Source: Venkatesh et al., 2012.

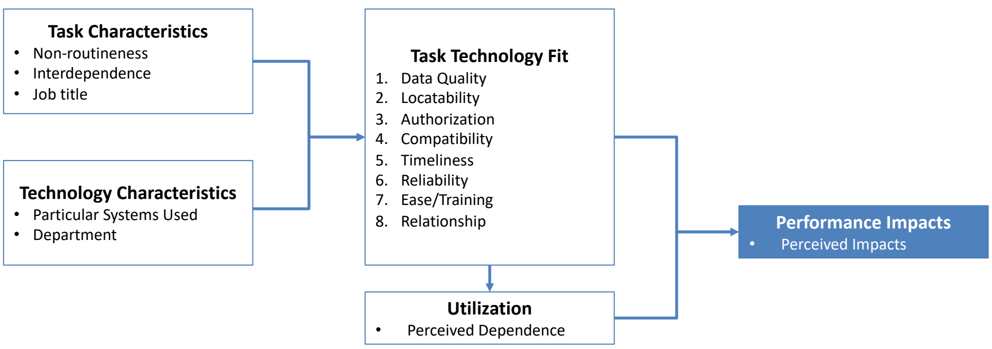
This updated version of the UTAUT model demonstrates that when performance expectations improve, along with social influence, favorable conditions, perceived hedonistic motivation, and the perceived value for the price, while also lowering the anticipation of effort, it leads to a heightened intention to use (Venkatesh et al., 2012). Nevertheless, when examining matters within organizations like the subject we are currently addressing (robotization at work), it's crucial to center our attention on emotional factors such as motivation, organizational commitment, talent attraction, and so forth. And these mentioned models are incomplete as they do not delve into aspects of an emotional nature, clearly linked to our robotization in the workplace. In fact, this model distinguishes between organizational and non-organizational environments (Yáñez-Luna, 2014), understanding that based on the expected effort of employees in each organization, the implications in terms of technological acceptance are different than with a "consumer" (Lin, C. et al., 2007).

The model explains how variables that currently are considered as basic such as age and user experience (UX) are determinant for acceptance. However, although both models (UTAUT and UTAUT 2) are very interesting to analyze technological acceptance of products for users/consumers, both present shortcomings to investigate the acceptance of the robot at work (Williams et al., 2015). Of course, they could be used, but their testing from an organizational and change management perspective, it would represent a challenge because they do not delve into emotional aspects, which can be understood are present in robotization processes (Stock-Homburg, R., 2022).

2.4.2 Other models and theories of technology acceptance

Thinking from a technology acceptance robotization at the workplace and its implications in terms of individual performance, the **Task-Technology Fit (TTF)** Model (Figure 2.37) is clearly oriented to tasks and individual performance. This model brings into attention that there must be an adequate fit between the technology and the specific task to be carried out.

Figure 2.37 TTF Model



Source: Goodhue & Thompson (1995).

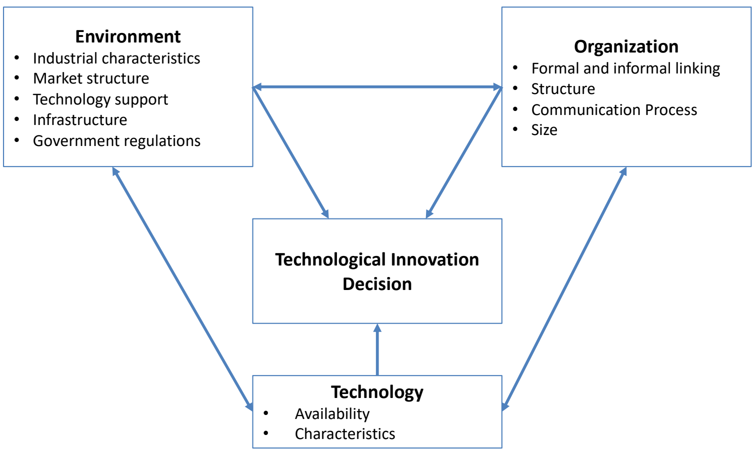
At this point, reference can be made as well to the **Technology-Organization-Environment** (TOE) (Tornatzky & Fleischer, 1990) displayed in Figure 2.38. This model is of particular interest in that it revisits a number of factors that condition the processes of innovation adoption and development in organizations and defines three relevant contexts for analysis:

Technological context which deals with the integration factors of the technologies relevant to the organization. In this sense, we must refer to both the new ones and those that have been in effect up to now.

Organizational context which deals with the specific characteristics of the company, such as the activity to which it is dedicated, the number of employees, the type of organization, the type of communication, as well as the resources available.

Environment context dealing with issues of competitive market organization, institutional relationships, suppliers and customers.

Figure 2.38 TOE Model



Source: Tornatzky & Fleischer, 1990.

In addition, we could refer to the **Technological Transition Model (TTM**), developed by Briggs et al. (1999). This model emphasizes the whole set of external variables that can affect the use or acceptance of certain technology. In the same way than the TAM model, the authors introduce the idea that the use of a technology depends on the intention of use that will be made of it. According to Cataldo (2012) "*intent to use is a (synergistic) multiplier of the perceived net value that a user could obtain, switching from one technology to another. And the perceived frequency of such net value*".

The TTM states that there are additional variables, both rational and non-rational, that influence the two factors previously exposed. Among others: affectivity, economy, politics, cognitive requirements, etc. Cognitive requirements would correspond with the required mental effort to use a certain technology. This can be replaced by Ease of Use.

In summary, the TTM model a more complex TAM model, since it is based on it, and articulates the importance of resistance or mental requirement when working with a new technology. Valid on its approach, we understand that it does not fit 100% to our research, since the definition of the mental requirement construct can be very diverse. In addition, in the case of robotization processes, the employee does not substitute one technology for another, because there are multiple scenarios. It can be changed the technology, the nature of the role, change of functions, etc.

The **Socio-Technical Systems Theory (STS)** was born in London at the Tavistock Institute (Trist & Bamforth, 1951). This theory represents more a "paradigm" than a "model" by itself. Even though, I have considered to include it into this point for its relevance in terms of contextualization and probably to be considered for future focused studies (specific for a company or an industry) more even considering the current context of Industry 5.0., STS is an interdisciplinary framework that examines the interaction between social and technical elements in a specific system that should be considered for any innovation initiative (Bednar & Welch, 2020). It focuses on understanding how social and technological factors influence each other and how they collectively shape a robotization process.

When it comes to robotization at work, here are some key points to consider from the STS perspective:

Work System Approach: From a socio-technical standpoint, work systems are regarded as a fusion of social and technical components that interconnect and exert mutual influence (Taylor, 1975). In the context of introducing robots, this approach underscores the importance of comprehending the dynamic interaction between robots (as the technical facet) and human workers (representing the social facet) within the working milieu.

Task allocation and work design: Robotization involves the automation of certain tasks previously performed by humans (Parasuraman & Sheridan, 2000). STS highlights the need to consider how the redistribution of tasks between robots and humans affects work processes, job roles, and skills required. It recognizes that while some tasks may be fully automated, others may still require human involvement or new roles may emerge that complement robotic capabilities (Chui et al., 2016).

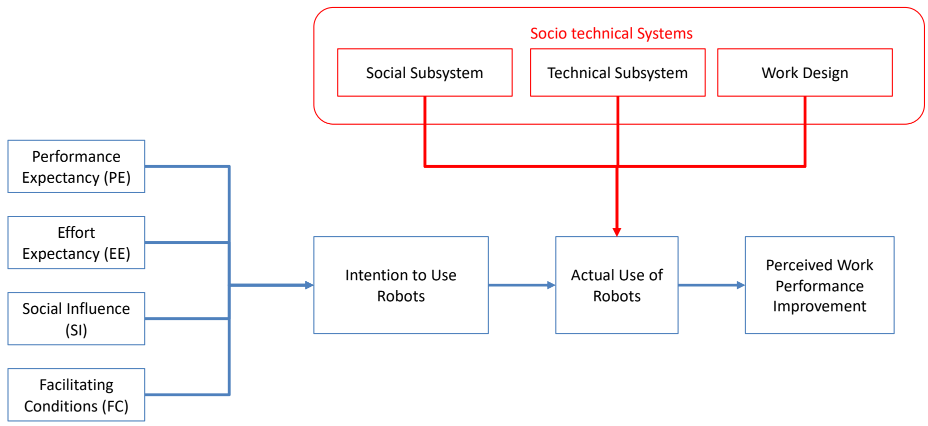
All this may imply providing training and support for workers to adapt to new technologies (Marler et al., 2006), addressing concerns about job displacement (Acemoglu & Restrepo, 2019), and considering the ethical and social impact of automation (Dwivedi et al., 2023; Lin et al., 2011). Factors such as communication, trust, and shared decision-making are highly recommendable to be considered (Molitor, 2020; Senge, 1990).

Prassida and Asfari (2022), applied a conceptual model for the acceptance of collaborative robots in a manufacturing environment, combining the UTAUT model with the STS. Regarding UTAUT definition in this case, there is no additional aspects to be mentioned because it has already explained in detail. In terms of STS, the definition was in the following terms:

- **Social subsystem**: as the company's capacity to change and adapt to robot's utilization.
- **Technical subsystem**: implementation environment and the integration level of cobots at the workplace.
- **Work design**: by the type of organization, use of teams, and tasks specialization.

In the merged model (UTAUT-STS) proposed by Prassida & Asfari (2022), as shown in Figure 2.39 these three factors (STS) mediate the actual use of robots.

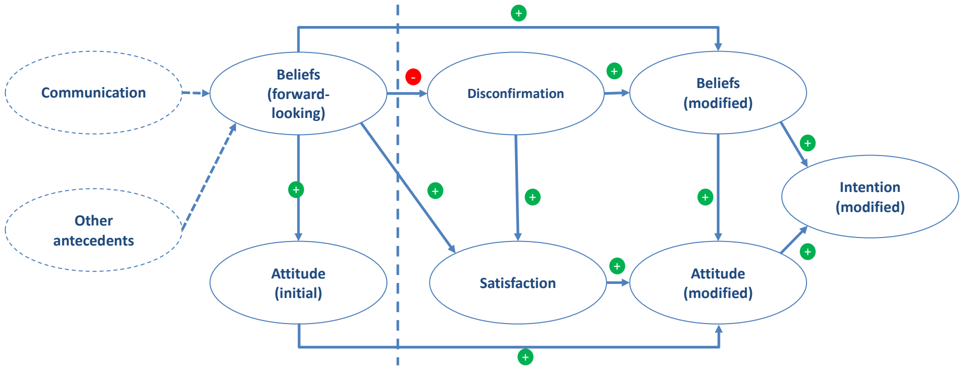
Figure 2.39 Conceptual model UTAUT-STS for robots in industry 5.0



Source: Prassida & Asfari, 2022

For those cases that it would be convenient to consider a longitudinal study in terms of technology acceptance, it could be performed based on the **expectation-disconfirmation theory (EDT)**. In Figure 2.40 is represented the model presented by Bhattacherjee and Premkumar (2004) where beliefs and attitudes can change from a previous a stage t^0 to a usage stage t^1.

Figure 2.40 A two-Stage Theoretical Model of Cognition Change (EDT)



Source: Bhattacherjee & Premkumar (2004).

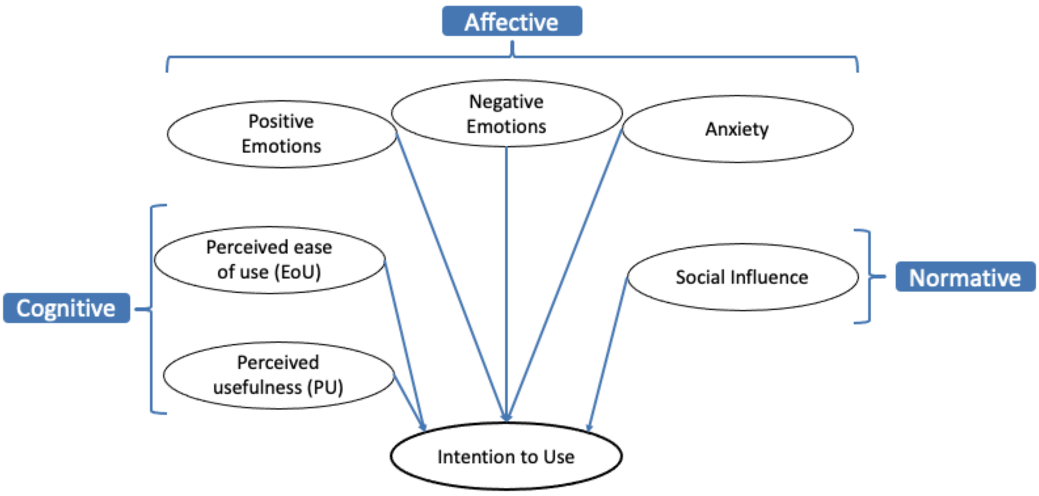
2.4.3 The Cognitive Affective Normative (CAN) model

The technology acceptance is socially constructed (Otway & Von Winterfeldt, 1982); (Malhotra & Galletta, 1999); (Venkatesh & Davis, 2000), and specifically the Cognitive-Affective-Normative model was developed more than five years ago, by (Pelegrín-Borondo et al., 2017) to explain individuals' intention to use insideables.

Since then, it has been extrapolated to other technologies and applications to explain acceptance towards new products or services, like beverages (Olarte-Pascual et al., 2017); (Reinares-Lara et al., 2023) cyborg technologies (Reinares-Lara et al., 2018); cryptocurrencies (Arias-Oliva et al., 2019); emerging methodologies in management education (Rodríguez-López et al., 2021); vaccines (Pelegrín-Borondo et al., 2021) or even closer to this research, the acceptance of social robots in retail industry (Subero-Navarro et al., 2022).

Originally based on the TAM (Davis, 1989; Davis, Bagozzi & Warshaw, 1989), and subsequent developments through the TAM2 (Venkatesh & Davis, 2000) bringing into attention affective and emotional factors. The **CAN Model** (Figure 2.41) combines three series of variables (Pelegrín-Borondo et al., 2017): **cognitive variables**, such as performance expectancy (PE) and effort expectancy (EE), together with variables of a **normative nature**, such as subjective norms. These subjective norms are key in organizations, and more even when the analyzed behavior is not volitional (Hwang et al., 2016), surprisingly, some research has showed that, despite there is a general individualism in Western countries, subjective norms show relevant influence on behavior intention (Schepers & Wetzels, 2007). And finally, the model incorporates **affective variables** categorized as positive emotions, negative emotions, and emotional anxiety towards the use of the specific technology.

Figure 2.41 Cognitive - Affective - Normative (CAN) model



Source: Pelegrín-Borondo et al. (2017).

As indicated, the initial focus lay on examining technological tools that, upon integration, enhance individual capabilities. This scenario appears apt for analogy in the context of the current research, given that one of the roles of robots in the workplace, aside from task substitution, should ideally contribute positively to overall human performance. To gain a deeper comprehension of the various ways in which the robot can influence human performance and how diverse forms of interactions might shape emotions, it is advisable to revisit once more the diagrams labeled under the Figure 2.15. This figure illustrates distinct categories of Human-Robot interactions.

As previously mentioned, the object of model (CAN) was closely related to social acceptance (norms), since the implantation of devices into the body to increase our capabilities is by default, subject to what we name social norms. In this sense, we can also note certain equivalence with the social, ethical, political and economic debate around robotization, to the extent that it affects to jobs, employability, nature of the tasks and human-robot interaction (as employee and as customer…). Finally, the affective analysis that this model allows, it is undoubtedly decisive in considering this one, as the best model to address this dissertation. Before a process of robotization would be in launched, management should understand the affective implications, in order to define the best strategy. Because, for sure the company decision will affect to the automation process itself, as well as to climate at work and the attraction to newcomers (Turban, 2001). What is known as attracting, retaining and motivating talent. Robotization represents an organizational change, and according to Prochaska et al. (1997), the different stages or processes which configures that change, include innovation, cognitive challenges, affective implications, evaluation, support, commitment, reinforcement, and environmental reengineering strategies.

A brief introduction of the constructs to be considered will provide some context to understand why the CAN model is the more convenient for current research.

Cognitive constructs, developed by Davis (1989, p. 320) in his TAM model, and defined perceived usefulness (Performance Expectancy -PE-) as "*the degree to which a person believes that using a certain system would enhance his or her performance*". On the other hand, ease of use (Effort Expectancy -EE-) is defined as "*the degree to which a person believes that using a particular system would be free of effort*" or the effort that a person has to use to learn how to use a robot, or interact with it, or assuming new tasks. These constructs were also tested in TAM 2 by Venkatesh and Davis (2000).

The interpretation of these constructs in terms of robot's acceptance has also been tested by Schnall & Bakken, 2011; Parvez et al., 2022; Nguyen, 2022 and Jacob, 2023. According to Pelegrín-Borondo et al., (p. 105, 2017), "*several studies have empirically confirmed that TAM models explain in a consistent manner, approximately 40% of the variance, of the intention to use technological innovations*". Thus, the theoretical-empirical base as well as the constructs is proven.

Normative constructs or social norms, (subjective norms) refers to the pressure that is exerted from the social context for the acceptance or non-acceptance of a certain behavior (Ajzen, 1991).

The social influence is established in the subjective norm, from the Theory of Reasoned Action (Fishbein & Ajzen, 1975), TAM2 (Venkatesh and Davis, 2000), TPB (Ajzen, 1991)/ DTPB (Taylor & Todd, 1995) C-TAM-TPB (Xie et al., 2017), in the social factors -MPCU- (Thompson et al., 1991) and the Image -IDT- (Tornatzky & Klein, 1982), all acceptance models already exposed in the previous sub-chapter-. The significance of factors associated with social influence appears apparent, particularly when considering the adoption of a technology. Turja and Oksanen (2019) demonstrated how the acceptance of robots in the workplace is influenced by social norms, with variations based on the country of origin. Choices influenced by social norms can yield either positive or negative outcomes. For instance, in an environment where technophobia prevails or concerns about job loss are high due to inadequate employment prospects, the social context might resist collaborating with machines due to perceiving them as a potential threat. Moreover, it's important to consider the viewpoints of senior colleagues in the workplace, recruiters, or experts who can propagate their opinions through news outlets and social media platforms.

Affective constructs or influence of emotions when using a new technology. In general terms, there is ample empirical evidence that the decision-making process is affected by emotions that are the manifestation of thoughts, ideas, internal values and attitudes (Alonso Puig, 2012; Goleman, 1995).

In addition, this influence is also analyzed and recognized in relation to the interaction and work with robots, decisively affecting when deciding about it (Hollon & Rogol, 1985; Stock-Homburg, 2022; Zacharaki et al., 2020). Based on HRI theories, it has been shown that there multiple perspectives and which influence on employee's emotions based on multiple factors: some of them very generic like ethics, heath, safety, data ownership (Gauttier, 2019; Viseu, 2003); as well as the type of assigned role or responsibilities (Bratman, 1992; Scholtz, 2003; Segura et al., 2021); friendly-language or User-Experience as employee (Villani et al., 2018).

Within the affective construct, the elements that the CAN model measures are:

•Positive Emotions (PEm)

•Negative Emotions (NEm)

•Emotional States of Anxiety (AEm)

The definition of the concept of emotion in the CAN model is established by the Componential Emotion Theory, requiring a minimum common trait to identify the concept of emotion in the human being (Ortony & Turner, 1990; Russell, 2003; Scherer, 2001; Scherer, 2005). We would be referring to the need of stimuli, the cause or attribution of these stimulus, the physiological reaction, feelings of pleasure or displeasure and qualitative feelings of uniqueness. In short, tendency towards characteristic actions and emotional processes of short duration, knowing that emotions influence on behaviors and the originated action afterward. Some emotions have been shown to incite action, while others inhibit, change it or just make it disappears (Cohen et al., 2008; O'Neill & Lambert, 2001). In general, and according to (Pelegrín-Borondo et al., 2017) "*objects causing positive emotions are evaluated favorably, whereas objects causing negative ones are evaluated unfavorably*." (Bagozzi et al., 1999; Mano, 2004).

In short, evidence has been provided from the field of empirical research about how emotions are inherent in any robotization process. The commitment to use of the CAN model, has a lot to do with this construct, since other pure models such as TAM, TAM 2, etc. provide very interesting aspects, in the cognitive or normative, but we understand, that they lose faculties in the emotional, aspect, which is demonstrated, is vital to understand the emotional process that will always be associated with a process of robotization and human-robot interaction.

CHAPTER 3. METHODOLOGY AND PROPOSED MODEL

3.1 General review

In the previous chapter, it has been addressed the conceptual and bibliographic review based on robotics under different perspectives (concept, typology, human-robot interaction). Likewise, have been reviewed methodologies about technology acceptance, obviously centered in the Cognitive-Affective-Normative model.

To carry out all this literature review, has been considered the following research domains: "robotization", “robotics”, “automation”, “digitalization”, “technology acceptance” and “CAN model”. But it has also been necessary to resort to terms such as “human-robot interaction”, "Industry 4.0", "4IR", "I4.0", even “I5.0” and “intelligent automation”.

It is well known that some of the emerging research arises from conference papers (Sarkis, 2012), and more even considering the fast-moving tendency in our topics. For that reason, have been looked into detail conference proceedings, enriching vision, and providing a deeper analysis about findings.

To construct this literature review, it drew from prior efforts in the research article titled "*Industry 4.0, Robotization, and Corporate Reputation: A Systematic Literature Review*" (Montero-Vilela et al., 2022). This experience served to enhance the understanding of essential concepts and refine bibliographic analysis techniques, following the framework proposed by Denyer and Tranfield (2009) within the CIMO method (Context, Intervention, Mechanism, Outcome).

The field of technology acceptance is strongly linked to organizational change management (Mulet Alberola & Fassi, 2022), with a prominent available content from consultancy firms, management analysts, and literature (Turja & Oksanen, 2019; Willcocks & Lester, 1994).

3.2 Data sources

In this dissertation, four main sources have been used:

(1) Scientific papers, books, PhD dissertations, magazines, and other documents, paying attention to academic articles in premier journals in the field of business management, human resources, technology acceptance, robotics, and automation intelligence among others. These documents have been reached from: Web of Knowledge (WoK), Web of Science (WoS), Emerald, SCOPUS, ProQuest, Google Scholar and JSTOR using combined key words already indicated. Once revised literature, it has been analyzed and incorporated accordingly. In addition, some newsletters from institutions, associations, and consulting firms like International Federation of Robotics.

(2) Indexes and databases as secondary sources: Statista and International Federation of Robotics.

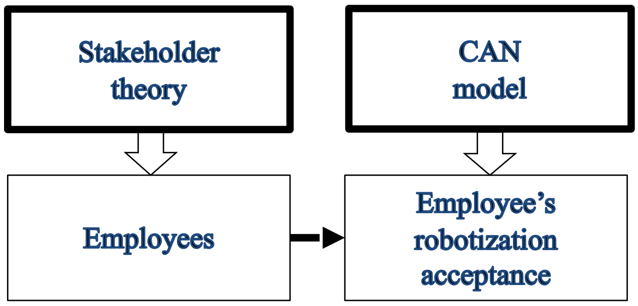
(3) Cases of study and reports to link practitioners' findings with literature (Yin, 2009). These business cases and reports came from the International Federation of Robotics as well as consultancy firms or Think Tanks like Deloitte, DPO, Randstad, McKinsey, PwC and the World Economic Forum.

(4) As primary source it has been performed a **general questionnaire** (Annex 2; Annex 3; Annex 4) of which technical details are available in Table 4.2, and analyzed under the chapter RESULTS. The ethical and privacy data aspects of this source have been revised and validated by the Ethical Committee of the Universitat Rovira i Virgili (Annex 12).

3.3 Proposed model

After this previous review, it has been shown that the two elected constructs (robotization and technology acceptance) have brought huge interest in academia, but not jointly. What justifies the convenience of this research and model.

Figure 3.1 Theoretical framework for analysis



Source: Own development

Supported by the **Stakeholder theory** (Barnett et al., 2006; Chun, 2005; Freeman, 1984; Mahon, 2002), the employees are considered as key stakeholders (Hall, 1992; Parvez et al., 2022), and protagonists of such innovation process (Schaarschmidt, 2016) as well as key players of the organizational transformation (Iverson, 1996).

Table 3.1 Segments of stakeholders

Internal stakeholders	Employees and senior managers of an organization.
Semi-external/internal (connected)	Individuals who are not entirely internal or external to a company such as potential employees, former employees, board members, shareholders, partners or unions.
External stakeholders	People outside of a company such as customers, clients, suppliers, NGOs, public entities, universities, and regulators.

Source: Own development based on Harvey & Morris (2012) p. 345

As a second block and main body of this study, it has been considered the acceptance by employees. Having evidence that one of the main barriers to implement robotizations, are the staff constrains and user resistance (Flechsig et al., 2022;

Garsombke & Garsombke, 1989), the present study explores the technology acceptance under the **CAN technology acceptance model**. This model has been chosen because of its affective constructs (positive emotions, negative emotions, and anxiety), since other models are very powerful in cognitive or normative variables, but are not able to address emotional issues, which for this research becomes essential, as finally expect connecting with emotions.

3.3.1 Design

The study sample (through the questionnaire) has been defined under the Cognitive-Affective- Normative (CAN) model by Pelegrín-Borondo et al. (2017), which was initially born to explain people's intention to use technological devices to increase innate capacity. The proposed model is based on previous technology acceptance models as TAM (Davis, 1989; Davis et al., 1989) and TAM2 (Venkatesh & Davis, 2000), representing an expansion which combines cognitive variables like perceived usefulness and perceived ease of use, as well as normative variables both subjective and social. As already highlighted, the main reason for having chosen the CAN model is because includes the affective component, what represents an added value for this study, if compared to other innovative acceptance models, especially when we refer to change management (Rodríguez-López et al., 2021), affording variables like positive emotions, negative emotions, and emotional states of anxiety.

The questionnaire was addressed to individuals in working age, over 18 years without any geographical restriction, trying to reach a global sample. The initial planned distribution was determined to avoid any bias on data, addressing it to diverse profiles in terms of job nature, geographical location, industry, and years of professional experience.

Despite the questionnaire didn’t ask for the specific role or profession, it is known that the study includes as well civil servants, as far as governments and public administrations require and experience a strong process of digitalization (Dunleavy et al., 2006; Johansson et al., 2023), being valuable their opinion to get an overall picture.

The age of the participants (over 18) may seem low, but this decision was based on the fact that it is the legal age in most of the countries. Despite most of them at that age still studying or work on part time or temporary basis. In any case, their input is relevant since they represent future generations that will face a labor market much more robotized than today. In addition, this criterion has been validated as well by the Eurobarometer sample, in its latest study about automation in EU, which was address even to citizens over 16 years.

As already mentioned, this CAN model has been already tested in topics linked to **socially acceptable** (*norms*), as implanting a device to increase capacities in the body (Olarte-Pascual et al., 2015; Reinares-Lara et al., 2018). In addition, the cognitive variables which are present in all models of technological acceptance, consider the **mental effort** to assess if a new technology becomes worthwhile or not. In terms of **emotions**, will be developed later on. Because of that, this model fits perfectly with our topic “robotization at work”, in the sense that there are organizational tendencies, a social perception and general opinion on these regards.

The questionnaire had three components:

(1) Questions related to the technology acceptance as such. Survey items (n = 24) based in the TAM/CAN model adapted from previous questionnaires. Each item had to be rated on a 11-point Likert scale (strongly agree=10 // strongly disagree=0).

(2) Items related to emotions, based on CAN model. Survey items (n = 20). Each item had to be rated on a 11-point Likert scale (feel intensely=10 and don't feel at all=0).

(3) Independent variables to determine if the participant has already worked with robots, which type of HRI has had (if any), and which interaction would like to have in the future (Scholz, 2003). In addition, there were demographic questions related to age and gender (Wang et al., 2020). To conclude, some professional information was requested in terms of number of years worked (Kim, 2008).

Once completed the questionnaire, participants had the opportunity to indicate an email address to receive an executive summary of the survey results and conclusions. Participants were also invited to share the questionnaire with colleagues, friends, or family.

3.3.2 Explanatory variables

Taking into consideration that our research is focused on RAW, it must be recognized that measurement scales for technological acceptance of Robots at Work, have not been an easy choice. Analyzed the different models of technological acceptance like TAM and its extensions TAM2 and TAM3, together with derivations from UTAUT2, it was required to fine-tune the eligible constructs, from just a pure technical conceptualization to a more work-related and social approach.

Have not been considered items related to price/cost, as employees do not incur in any economic expense because of the incorporation of robots. In the same way, have been excluded aspects as hedonism or habit because it is an imposed decision by the company. Nevertheless, other elements like emotions have been incorporated, paying special attention to the fear and the perceived risks that robotization at work may generate.

In the sense that robotization may represent an additional challenge in the workplace, a threat of losing the job or simply a negative perception in terms of employability. We should pay attention to negative emotions and states of anxiety.

Final determinant variables considered for this study are intention to use, performance and effort expectancy, social influence, attitude, perceived risk, facilitating conditions and emotions.

Performance Expectancy (PE)

Human-Robot Interaction brings a perfect and productive mixture, between cognitive capabilities and natural dexterity from humans, together with the accuracy and repeatability capabilities of the robot (Segura et al., 2021). As an example, there are extremely sensitive professional fields like surgery, that has already given a prominent room to robotics, especially in microsurgeries, surgical trainings and of course, simulations (Howe & Matsuoka, 1999). In the last two decades, the “joint venture” between Doctors and Robots, have advanced in an incredible manner, and latest news come from Spain. In April 2023 at Vall d’Hebron Hospital in Barcelona, a team of surgeons have performed the world’s first lung transplant operated by robots, following the indications from the human team (Min & Reuters/AFP, 2023). In words of the Chief surgeon, "*the precision of movements performed by the robot are unattainable by a human. We decide, and the robot is our hands*. *A perfect fit*"

But the impact on performance is not always as evident, as for instance, in the case of physic or mental fatigue. Some tasks traditionally performed by humans imply an inevitable progressive decrease in terms of quality and motivation (Segura et al., 2021) but in most of the cases, the negative tendency is not as easily observable.

Even the HRI or the use of technology in terms of performance, is not always perceived as positive (Nickerson, 1981). The employee can feel confused or stressed because of required learning processes, or just because of interacting with a machine, and sometimes robot's "power" can be perceived as a threat. Some other circumstances can affect negatively as well, like the speed of action of the device, movements around the employee (proxemics) or not perceiving the robot as a teammate (Parra et al., 2020).

Based on the TAM model (Davis 1989; Davis et al. 1989), we should understand that under the lens of "perceived usefulness", a certain technology can improve performance (Figure 2.32), even been considered as a generator of extrinsic motivation (Davis et al., 1992). Because a better fit in the job thanks to the use of technology, improves individual performance (Thompson et al. 1991), thus working with them is better than working without them (Moore & Benbasat, 1991). On top, such improvement can often be translated into personal benefits like a higher economic compensation, an internal promotion or improving his/her employee branding "*If I perform better, I am a better professional*".

At this point, and based on Compeau and Higgins, 1995[a] and Compeau et al. 1999, it should be differentiated between those performance expectations related and based just on the job (green in Table 3.2), and those expectations related to personal interests or individual objectives (red in Table 3.2).

Table 3.2 Performance Expectancy: literature and items' review

Construct	Source and Authors	Definition	Items
Performance Expectancy (PE)	Venkatesh, V., Thong, J. Y., & Xu, X. (2012). UTAUT2	The degree to which using a technology will provide benefits to consumers in performing certain activities.	-I find mobile Internet useful in my daily life. -Using mobile internet increases my chances of achieving things that are important to me. -Using mobile internet helps me accomplish things more quickly. -Using mobile internet increases my productivity.
Perceived Usefulness of working with robots	TAM scale Davis 1989; Davis et al. 1989	The degree to which a person believes that working with robots would **enhance his or her job performance**.	-Working with robots would enable me to accomplish tasks more quickly. -Working with robots would improve my job performance. -Working with robots would increase my productivity. -Working with robots would enhance my effectiveness on the job. -Working with robots would make easier to do my job. -I would find working with robots useful in my job.
Extrinsic Motivation for working with robots	Davis et al. 1992	The perception that users will want to work with robots because it is perceived to be instrumental in achieving valued outcomes, such as **improved job performance, pay or promotions**.	Extrinsic motivation is operationalized using the same items as perceived usefulness from TAM (items from 1to 6). -Working with robots would enable me to accomplish tasks more quickly. -Working with robots would improve my job performance. -Working with robots would increase my productivity. -Working with robots would enhance my effectiveness on the job. -Working with robots would make easier to do my job. -I would find working with robots useful in my job.
Job-fit in case of working with robots	Thompson et al. 1991	How the capabilities of working with robots **enhance an individual's job performance**.	-Working with robots will have no effect on the performance of my job (reverse scored). -Working with robots can decrease the time needed for my important job responsibilities. -Working with robots can significantly increase the quality of output on my job. -Working with robots can increase the effectiveness of performing job tasks. -Working with robots can increase the quantity of output for the same effort. -Considering all my tasks, the general extend to which working with robots could assist on my job... (adjusted scale for this item).
Relative Advantage of working with robots	Moore & Benbasat 1991	The degree to which working with robots is perceived as being **better than without them**.	-Working with robots enables me to accomplish tasks more quickly. -Working with robots improves the quality of the work I do. -Working with robots makes easier to do my job. -Working with robots enhances my effectiveness on the job. -Working with robots increase my productivity.
Task-Technology Fit	Goodhue & Thompson, 1995	The degree to which a technology assists an individual in performing his or her portfolio of tasks.	-The company computer environment has a large, positive impact on my effectiveness and productivity in my job. - IS computer systems and services are an important and valuable aid to me in the performance of my job.
Outcome expectations of working with robots	Compeau & Higgins, 1995b; Compeau et al. 1999	Outcome expectations related to the consequences of the behavior. Based on empirical evidence, they were separated into performance expectations (-job-related) and personal expectations (-individual goals).	If I work with robots... -I will increase my effectiveness on the job. -I will spend less time in routine tasks. -I will increase the quality of output of my job. -I will increase the quantity of output for the same amount of effort. -My coworkers will perceive me as competent. -I will increase my chances of obtaining a promotion. -I will increase my chances of obtaining a raise.

Source: Own Development based on the authors.

Under Performance Expectancy (PE), the employee could consider: the increase in terms of speed performing tasks, the assumption of more complex tasks, increasing productivity, being perceived as more effective, getting a promotion or a salary increase, among others. The perception of the employee about this specific construct, it will depend mainly on his/her goal orientation (Molino et al., 2020).

This construct is defined as the *degree to which an individual believes that working with a robot will help him or her to attain gains in job performance*.

In Table 3.3, the questions included in the questionnaire to address this construct.

Table 3.3 Performance Expectancy and Robotization at Work

Items
PE1 I would consider useful to work with robots daily.
PE2 Working with robots would increase my chances of achieving important performances.
PE3 Working with robots would allow me to perform tasks more quickly.
PE4 Working with robots would increase my productivity.

Source: Own development based on Venkatesh et al. (2012). UTAUT2 scale

Effort Expectancy (EE)

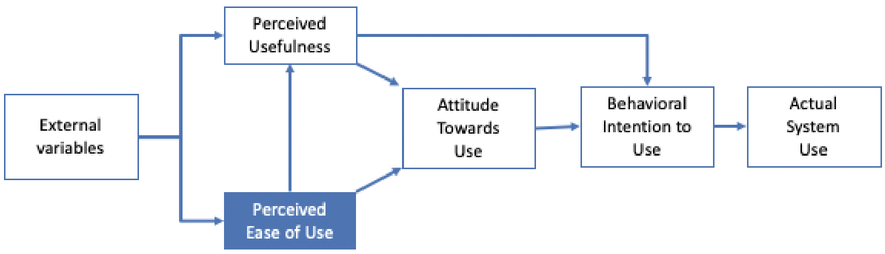
According to the International Federation of Robotics, the ability to manage industrial robots with no prior programming experience nor knowledge is now easier than ever. Companies can use software-driven automation platforms to manage industrial robots. Manufacturers work together with technology partners to offer equipment who require low-code or even no-code programming capabilities, making robot programming accessible to all skill levels. The utilization of easy-to-use software combined with an intuitive user experience eliminates the requirement of extensive robotics programming and enhances robotic automation possibilities. In addition, all interfaces and systems are much more user-friendly and safer (understood as safety at work) than before.

The use of sensors and updated software allow to setup and to operate traditional heavy-weight industrial robot as collaborative. By combining robust, precise industrial robot hardware with the latest cobot software, companies will benefit from the best of both worlds. Low-cost robotics is also characterized by easy-to-use programming interfaces, enabling customers to set up robots by themselves.

As a result of the pandemic in 2020, many new companies have tried robotic solutions. Robot suppliers recognized the niche for lower-cost robot, for instance, by providing pre-configured software to manage sensors.

Effort Expectancy (EE) can be determined depending on the degree of perceived ease in the use of a certain technology (Ease of Use · EoU). This is measured in terms of ease of working with such technology, considering the amount of effort to be made by the individual (Davis, 1989; Davis et al., 1989). The degree of complexity is also relevant for this construct.

Figure 3.2 Technology Acceptance Model (TAM) and Perceived Ease of Use



Source: Davis, Bagozzi and Warshaw (1989).

The effort expectancy (EE) has also been measured in terms of difficulty that the adoption of a certain technology may represent (Thompson et al. 1991; Moore & Benbasat 1991). To assess the required effort, would be decisive to consider how ease becomes the interaction with this new device, as well as individual abilities (Table 3.4).

Table 3.4 Effort Expectancy: literature and items' review

Construct	Source and Authors	Definition	Items
Perceived ease of working with robots	TAM scale Davis 1989; Davis et al. 1989	The degree to which a person believes that working with robots would be **free of effort**.	-Learning to work with robots would be easy for me. -I would find easy working with robots to do what I want them to do. -It would be easy for me to became skillful at working with robots. -I would find working with robots easy to do.
Complexity of working with robots	Thompson et al. 1991	The degree to which working with robots is perceived as relatively **difficult to be understood** and do it.	-Working with robots requires too much time from my normal duties. -Working with robots is so complicated, difficult to know what is going on. -Working with robots implies too much time doing mechanical operations. -It takes too long to learn how working with robots to make it worth the effort.
Easy of working with robots	Moore and Benbasat 1991	The degree to which working with robots is perceived as being **difficult to do** it.	-My interaction with the robot is clear and understandable. -I believe it is easy to get the robot to do what I want it to do. -Overall, I think the robots are easy to use. -Learning to operate the robot is easy for me.

Source: Own development based on the authors

This factor (EE) applied to RAW, it can be understood from a double perspective: employee's resources like capability to work with robots, and on the other hand, those resources that depends on others (company), as training or development when they are going to be exposed to a new technology, specifically those that are related to the use of the tool. Because it makes possible that employees could fit better with the role, as well as developing positive attitudes and feelings towards robots (Marler et al., 2006).

This construct is defined as the *degree to which an individual believes that working with a robot would be easily achievable (required effort from his/her side)*.

Below (Table 3.5), the questions included in the questionnaire for this construct.

Table 3.5 Effort Expectancy and robotization at work

Items
EE1 Learning to work with robots would be easy for me.
EE2 My interaction with robot would be clear and understandable.
EE3 It would be easy to work with robots.
EE4 It would be easy for me to become skillful at working with robots.

Source: Questionnaire based on Davis 1989; Davis et al., 1989; Moore & Benbasat, 1991.

Social Influence (SI)

Determined by the relevance that supposedly other people (family, friends, and social environment in general) give to the fact that an individual uses a certain technology. Into this review and further analysis, have been considered subjective or cultural norms, social factors and image perception, as external variables to the employee.

Social Influence (Figure 2.33) was based on the analysis of factors related to the individual's perception about what other people who are important (subjective norms) think in relation to whether or not having a certain behavior (Ajzen, 1991; Davis et al. 1989; Fishbein & Azjen, 1975; Mathieson 1991; Taylor & Todd, 1995[a] 1995[b]; Venkatesh & Davis, 2000). The social norm reflects the pressure that is exerted from the social sphere towards behaviors (Ajzen, 1991).

In relation to this construct, the intention to do something is a mix between our attitude towards such technology and the subjective norms (normative beliefs coupled with the motivation to please others).

Likewise, social influence is built based on social factors and individual's conviction about the culture in the social group, together with some other interpersonal agreements (Thompson et al., 1991). Sometimes working with certain technologies, it can be translated into a better image or status within a social environment (Moore & Benbasat, 1991).

In Table 3.6 are shown the main theories and items related to this construct.

Table 3.6 Social Influence: literature and items' review

Construct	**Source and Authors**	**Definition**	**Items**
Subjective norm	TAM2 scale Venkatesh & Davis, 2000 Ajzen 1991; Davis et al. 1989; Fishbein and Azjen, 1975; Mathieson 1991; Taylor and Todd, 1995a 1995b.	The person's perception that most people who are important for him/her think he/she should or should not perform a specific behavior (working with robots).	-People who influence my behavior think that I should work with robots. -People who are important for me think that I should work with robots.
Social factors	Thompson et al., 1991	The individual's internalization of the reference group's subjective culture and specific interpersonal agreements that the individual has made with others, in specific social situations.	-I work with robots because of the proportion of coworkers that they do that. -The senior management of this business has been helpful and supportive in the robotization process. -My supervisor is very supportive of working with robots for my job. -In general, the organization has supported working with robots.
Image	Moore & Benbasat, 1991	The degree to which working with robots is perceived to enhance one's image or status in one' social system.	-People in my organization who work with robots have more prestige than those who do not. -People in my organization who work with robots have a high profile. -Working with robots is a status symbol in my organization.

Source: Own development based on authors

If we focus this social influence or the subjective norm into our specific research, it would be convenient to be aware about two types of contexts:

First, **robotization processes has an evident impact on employment** (Autor & Salomons, 2018; Acemoglu & Restrepo, 2019; Faber, 2020; Frey & Osborne, 2017;

Payne & Lloyd, 2019; Vermeulen et al., 2018). In this case, it would be strongly influenced by social norms: like social networks' input, news, as well as our closest people's thoughts and concerns. In this case, it could be assumed that individuals would receive messages encouraging to stay in low-tech environments to avoid risks. But on the contrary side, our people could have a completely different approach, inviting us to blend in, because in this way, we will be able to handle in a more fluid way in the labor market.

Secondly, **been aware that robotization at work is usually mandatory** for employees -instead of voluntary- (Hwang et al., 2016; Turja & Oksanen, 2019), this will bring a completely different approach for analysis, if compared for instance, with consumers' acceptance and social norms. In this specific case, the normative construct should be considered as less relevant.

Nevertheless, social influence is a key construct for the different technology acceptance models (TRA, TPB, TAM2), becoming relevant as well for our robotics' acceptance research. This is because in a robotized context, employability of the people can be improved working with robots, and individuals can be influenced by others (parents, peers, and senior professionals) to get a new job or remaining in the current one (Kulkarni & Nithyanand, 2013).

In Table 3.7, the questions included in the questionnaire for this construct.

Table 3.7 Social Influence and robotization at work

Items
SI1 People who are important to me, think I should work with robots
SI2 People who influence my behavior think I should work with robots
SI3 People whose opinions I value, would prefer that I would work with robots

Source: Questionnaire based on TAM2 and UTAUT2 scale (Venkatesh et al., 2012; Venkatesh & Davis, 2000; Ajzen, 1991; Davis et al., 1989; Fishbein & Azjen, 1975; Mathieson, 1991).

Perceived Risk (PR)

Perceived risk is a well-studied construct in relation to Robot Acceptance at Work (Frey & Osborne; 2017). which appear where probabilities of outcomes are not known, and the outcome is known or unknown (Im et al, 2008). When a society embraces robotization, may also produce **fear** about employment as threatening and competitive for current or future employees (Jörling et al., 2019; Paluch et al., 2022), especially for those low-end skilled jobs (Saner & Wallach, 2015), and even there are some financial implications around from a personal or family perspective (McClure, 2018).

Despite the meaning of risk can be linked to multiple factors, in terms of robotization, it has mostly analyzed as a threat for employment. In that sense, the more employees feel threaten their employment, less acceptance towards robotization (Vu & Lim, 2022). But human psychology is complex, and a study from the Technical University of Munich (TUM) and Erasmus University in Rotterdam, shows that employees would prefer to be replaced by a robot than by another human. This feeling has its based on their own self-worth (Granulo et al., 2019).

As summary, no clear overview in this sense. Because recent studies shows that most of the population (men and women) are not really convinced about the idea of collaborating with a cobot, while some other research (as a survey conducted by Oracle, reveal that 90% of the employees would trust on a cobot (Pullach et al., 2022), and it has already demonstrated that trust in robotics represents a positive prediction of robotization acceptance (Ciğdem et al., 2023). In general terms and from a global perspective, there is a higher acceptance of robots at work, in those countries with lower job automation risk (Turja & Oksanen, 2019).

To gain a deeper insight into the varying individual attitudes regarding the acceptance of robots in the workplace, Stephen Covey's model (Figure 3.3), which differentiates between the circle of concern, circle of influence, and circle of control, can offer additional context in this regard.

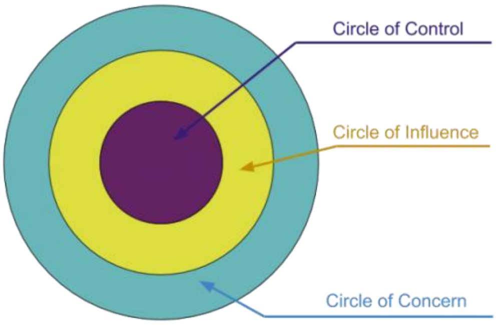
About the **circle of control**, there is nothing to be said at this point. If the employee feels that everything is under control, the perceived risk will be zero.

When examining perceived risks, it becomes crucial to investigate how individuals navigate both their **circle of concern** and circle of influence. The former encompasses a broader spectrum, encompassing issues over which individuals may not believe they have any significant control. In this context, we encounter reactive individuals who predominantly experience feelings of powerlessness. Examples might include thoughts like, "*I'm almost certain the company will choose to lay me off once the robot becomes operational*" or "*There's a high likelihood I'll have an accident with the robot moving around me…*".

Within the **circle of influence**, we encompass those emotions and situations over which we have the capacity to act. This is where proactive individuals thrive, demonstrating initiative and the capability to respond, gradually expanding their sphere of influence, as articulated by Covey (1989). As an individual's sphere of influence expands, their circle of concern naturally shrinks. This phenomenon occurs because when you are able to exert influence on something, it becomes of lesser concern to you.

This reflection bears relevance concerning the subject of our study because it hinges on how employees, or even those who hold influence over them, approach the concept of robotization. Such an approach can lead employees to perceive robotization either as a genuine threat or as an opportunity. For example, taking the previous sentences into account, an employee might believe that becoming an expert in robotics would reduce the likelihood of the company laying them off. Alternatively, in comparison to colleagues who are resistant to change, they may see themselves as ideal collaborators on the work floor. Such self-attitudes indeed fall within their sphere of influence.

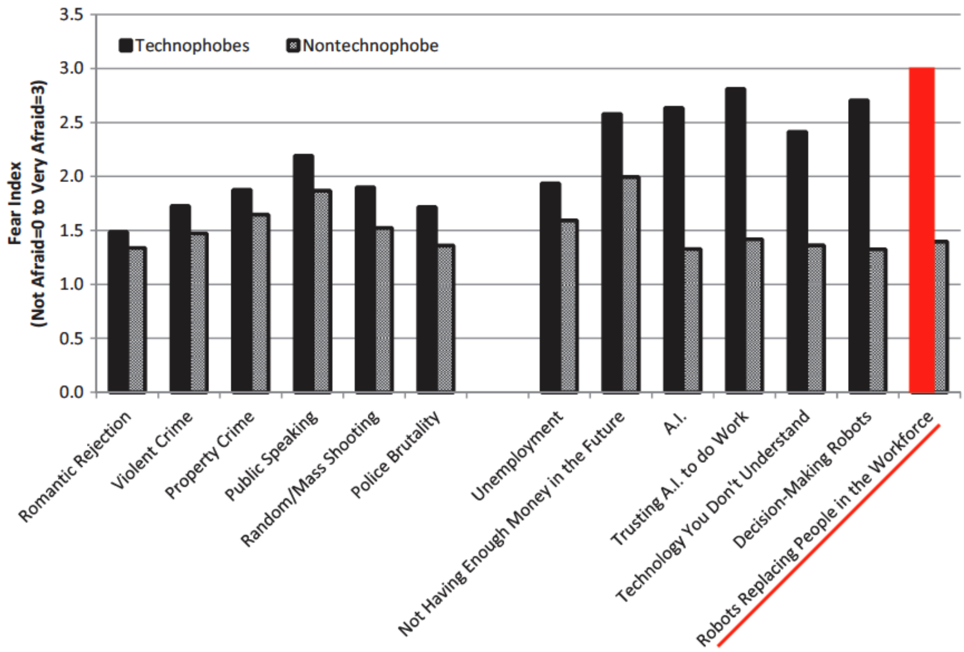
Figure 3.3 Circle of control, influence, and concern



Source: Covey (1989).

Bringing additional data to the topic, and focused on the American society (McClure, 2018), the item “Robots Replacing People in the Workforce” becomes the most feared item for those classified as Technophobes (see Figure 3.4), representing almost the double than for those who are classified as Non-technophobes. Technophobes brings higher levels of fear in every single category.

Figure 3.4 Fears of technophobes and non-technophobes



Source: Adapted from McClure (2018), based on Chapman Survey of American Fears (2015).

Beyond fears about impact on performance and employment, **safety at work** it should be considered as well as a critical factor, and one of the most relevant concerns for employees and authorities. In fact, most of the new methods and studies related to human-robot collaboration have been related to safety aspects (Bicchi et al., 2008; Zacharaki et al., 2020). In that sense, most of the governments and associations are aware. Beyond specific Health & Safety regulations at country level, the International Organization for Standardization, has defined a guidance for Human-Robot collaboration in the same workspace, as already shown in Table 2.7.

In Table 3.8, the questions included in the questionnaire for Perceived Risk.

Table 3.8 Perceived Risk about robotization at work

Items
Perceived Risk (PR)
PR1 Working with robots is risky.
PR2 Would be too much uncertainty associated with working with robots.
PR3 Compared with other jobs, those with robots are riskier.

Source: Questionnaire based on UTAUT model (Venkatesh & Davis, 2000).

Facilitating Conditions (FC)

Understood as the quantity or quality of resources available to use such technology, together with perceived control in terms of internal or external constraints, including self-efficacy and enabling conditions of resources and technology (Ajzen 1991; Taylor and Todd 1995a 1995b), and even understood as the support offered by the environment to facilitate such implementation (Thompson et al. 1991). Finally, worthy to be mentioned the compatibility of the applied technology with the values, needs and previous or expected experiences of the employees (Moore & Benbasat, 1991). See Table 3.9.

Table 3.9 Facilitating conditions: literature and items' review

Construct	Source and Authors	Definition	Items
Perceived behavioral control	Ajzen 1991; Taylor & Todd 1995a 1995b.	Reflects perceptions of internal and external constrains on behavior and encompasses self-efficacy, resources facilitating conditions and technology facilitating conditions.	-I have control over working with robots. -I have those required resources to work with robots. -I have the required knowledge to work with robots. -Given the resources, opportunities, and knowledge, it would be easy to work with robots. -Robots are not compatible with the current systems in the organization
Facilitating conditions	Thompson et al. 1991	Objective factors in the environment that observers agree make an act easy to do, including the provision of support.	-Guidance was available to me in the selection of the robot. -Specialized instruction concerning the robotization process was available to me. -A specific person (or group) is available for assistance with difficulties.
Compatibility	Moore & Benbasat, 1991	The degree to which an innovation is perceived as being consistent with existing values, needs and experiences of potential adopters.	-Working with robots is compatible with all aspects of my work. -I think that working with robots fits well with the way I like to work. -Working with robots fits into my work style.

Source: Own development based on above mentioned authors.

In Table 3.10, the questions included in the questionnaire for this construct.

Table 3.10 Facilitating Conditions and robotization at work

Items
FC1 I would have those required resources to work with robots.
FC2 I would have the required knowledge to work with robots.
FC3 Robots would be compatible with current systems and technologies in the organization.
FC4 In case of need, I would have support or assistance from others.

Source: Questionnaire based on Ajzen (1991); Taylor & Todd (1995b); Thompson et al. (1991).

Emotions (Em)

As already mentioned, emotions are included in the study because people have fears about robots (Nomura et al., 2006), having expectations as well in terms of required effort and performance (Park & del Pobil, 2013).

Affective constructs respond to emotions that reflect thoughts, ideas, internal values, and attitudes (Goleman, 1995). These constructs deserve a prominent place in our analysis, because as mentioned by Turner & Stets in 2005, strikes that these constructs had received so little attention from academia, despite permeating in every aspect of human experience.

The concept of emotion in the Cognitive Affective Normative (CAN) model is based on the Componential Emotion theory, which recognizes basic emotions in the human being. Aspects like the stimulus and its cause, as well as physiological reactions: pleasure, displeasure, and emotional processes of short duration (Ortony & Turner, 1990; Scherer, 2001; Scherer, 2005). According to the CAN Model and based on the PANAS scale, the emotions to be measured in this study are positive emotions (PEm), negative emotions (NEm), and emotional state of anxiety (AEm). (see Table 3.11).

Table 3.11 Emotions: literature and items' review

Construct	Source and Authors	Definition	Items/emotions		
Emotions produced by the idea of working with robots	PANAS scale Watson et al., 1988	Classified as positive (PEm), negative (NEm) and anxiety (AEm).	PEm1.- Interested PEm2.- Excited PEm3.- Determined PEm4.- Enthusiastic PEm5.- Proud PEm6.- Inspired PEm7.- Strong PEm8.- Active	NEm1.- Distressed NEm2.- Upset NEm3.- Guilty NEm4.- Ashamed NEm5.- Scared NEm6.- Hostile NEm7.- Afraid NEm8.- Irritable NEm9.- Alert	AEm1.- Nervous AEm2.- Attentive AEm3.- Jittery

Source: Own development based on Watson et al. (1988).

In this sense, it should be noted that the analysis of emotions, is generally focused on positive and negative, generating decisive attitudes in favor or against a certain behavior. From a scientific perspective, a positive value does not mean necessarily that it is good and negative the opposite. What is relevant is the polarity and its valence. Confusion between valences and values is easy and frequent. In science, positive means "presence of something." And negative is "absence of something".

Considering required training, new tasks to be performed, even reorganization at work, we assume that this robotization process (as a change process), brings a natural stres. And because of that, the items related to "anxiety" should be assumed and perceived as positive at a reasonable level to assess the RAW. This limited stress or tension; it can be positive to afford those kinds of situations.

In the present study we will refer to positive as the presence of emotions which may favor technology acceptance, or not. In positive terms, we consider interested, excited, determined, enthusiastic, proud, inspired, feeling strengthened and finally, active. On the other hand, as negative emotions: distressed, upset, confused, ashamed, scared, hostile, afraid, irritable, and alert. Finally, anxiety should be highlighted as a third category of emotions, which is reflected in terms of nervousness, staying attentive and jittery. All these emotions based on the idea of working with a robot.

The question about emotions and robotization at work (Annex III page 2), it was: *Think about how you feel/felt about working with a robot, and value the following adjectives from 0 you don't feel at all, to 10 you feel it intensely*.

Table 3.12 Emotions and robotization at work

Items	
PEm1	Interested
PEm2	Excited
PEm3	Determined
PEm4	Enthusiastic
PEm5	Proud
PEm6	Inspired
PEm7	Strong
PEm8	Active
NEm1	Distressed
NEm2	Upset
NEm3	Confused
NEm4	Ashamed
NEm5	Scared
NEm6	Hostile
NEm7	Afraid
NEm8	Irritable
NEm9	Alert
AEm1	Nervous
AEm2	Attentive
AEm3	Jittery

Source: Questionnaire based on PANAS scale. Watson et al. (1988).

Attitude (At)

Robotization in any organization entails a shift in work functions (Hawryluk & Rychlik, 2022). Although not everyone is impacted, at least a portion of the workforce may see a disruption in their regular work because of robotization (Kim et al., 2022). An underlying reluctance to change is frequent, especially in periods of severe disruption like current one (Miller, 2021). Attitude understood as personal affect toward working with robots (Bhattacherjee & Premkumar, 2004), this construct is fully pertinent to be included as part of the questionnaire. In fact, "attitude" will be the precedent of final RAW ("intention to use").

The attitude will be key to connect motivation of employees with business decisions. As shown in previous constructs, we should pay attention to beliefs and attitudes, because are decisive for the acceptance of technology and its subsequent use (Nomura et al., 2006). Based on the expectation-disconfirmation theory -EDT- (Oliver, 1980) and longitudinal studies, we already know that beliefs, feelings and attitudes of people exposed to technological environments, evolve over time (Morris et al., 1993; Bhattacherjee & Premkumar, 2004).

Annex 6Characteristics that may be pertinent in shaping an employee's stance regarding robotization, include resilience and goal-oriented behavior. (Molino et al., 2020).

In Table 3.13, the questions included in the questionnaire for this construct.

Table 3.13 Attitude and robotization at work

Items
At1 Using robots in the workplace would be a good idea.
At2 Using robots in the workplace would be a wise move.
At3 Using robots in the workplace would be a positive step.
At4 Using robots in the workplace would be an effective idea.

Source: Questionnaire based on Bhattacherjee & Premkumar (2004).

Intention to Use (IU)

Translated into this study as Robot Acceptance at Work (RAW) becomes the ultimate and key construct explanatory of attitude. According to Venkatesh & Davis (2000), is defined as the cognitive state of the employee's mind and their intention to work with robots. Intention to Use can fluctuate from a completely obligatory action to a completely voluntary one. While according to Trice & Treacy (1988), the more a system is used, greater the impact regardless of its obligation.

Considering that the decision to incorporate robots into the workplace is taken by the company's management (Molet et al., 1989), and irrespective of whether employees embrace it willingly or not, it becomes important to ascertain whether employees genuinely intend to work with robots or are simply doing so under compulsion. Understanding an individual's intention in this context is significant because it allows to predict the likelihood of acceptance and the subsequent behavior, they are likely to exhibit.

Annex 6

Table 3.14 Behavioral Intention to use literature and items' review

Construct	**Source and Authors**	**Items**
Intention to work with robots	TAM2 scale Venkatesh & Davis, 2000	-Assuming I have access to a robotized environment, I intend to work with them. -Given that I have access to a robotized environment, I predict that I would work with them.

Source: Own development based on Venkatesh & Davis (2000).

In Table 3.15, the questions included in the questionnaire for this construct.

Annex 6

Table 3.15 Intention to Work with Robots

Items
IU1 Assuming I have access to a robotized workplace, I intend would work on it.
IU2 In case I would have access to a robotized workplace, I predict that I would work on it.

Source: Own development based on Venkatesh & Davis, 2000

3.3.3 Hypothesis

In order to bring some conclusions about if employees accept to work with robots, we have formulated different hypotheses that derive from (1) the relationships established in the CAN model, (2) the context analysis, as well as from (3) the constructs and theories analyzed in relation to acceptance technology. All this, with a sample of participants from 18 to 80 years old with a global scope.

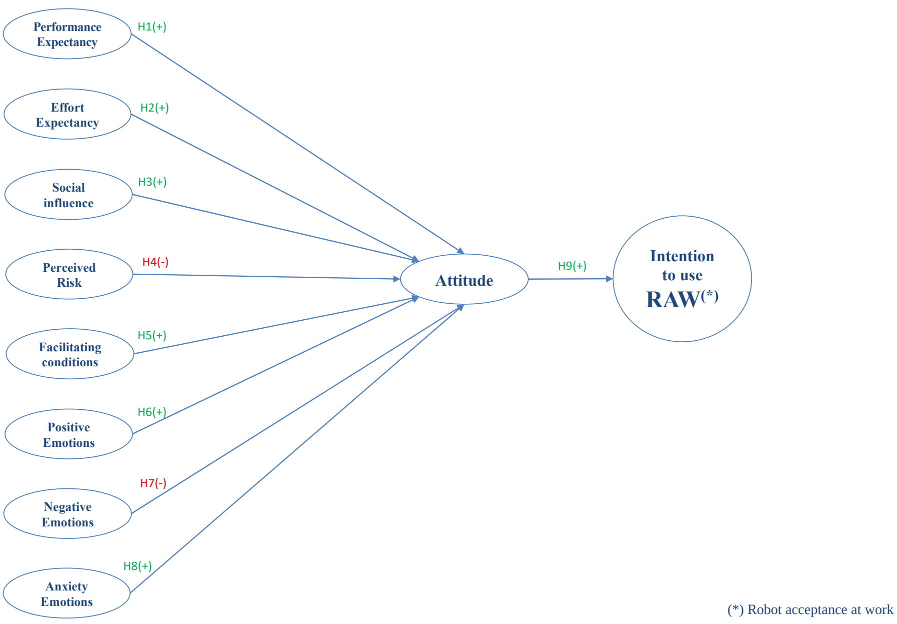
Table 3.16 Research hypothesis

Hypothesis 1	Performance Expectancy (PE) has a positive relationship with a positive attitude towards working with robots (At).
Hypothesis 2	Effort Expectancy (EE) has a positive relationship with a positive attitude towards working with robots (At).
Hypothesis 3	Social Influence (SI) has a positive relationship with a positive attitude towards working with robots (At).
Hypothesis 4	Perceived Risk (PR) has a negative relationship with a positive attitude towards working with robots (At).
Hypothesis 5	Facilitating Conditions (FC) have a positive relationship with a positive attitude towards working with robots (At).
Hypothesis 6	Positive emotions (PEm) have a positive relationship with a positive attitude towards working with robots (At).
Hypothesis 7	Negative Emotions (NEm) have a negative relationship with a positive attitude towards working with robots (At).
Hypothesis 8	Anxiety Emotions (AEm) have a positive relationship with a positive attitude towards working with robots (At).
Hypothesis 9	Attitude (At) has a positive relationship with intention to work with robots (IU/RAW).

Source: Own development

In Figure 3.5 are detailed the relations of all the hypothesis into the defined model.

Figure 3.5 The hypothesized model



Source: Own development

Additional details for each hypothesis are provided below:

Hypothesis 1: Performance Expectancy (PE) has a positive relationship with a positive attitude towards working with robots (At).

Robotization can be understood as a positive driver for employability and goals' achievement. Because the employee can learn and use the most innovative tools and has been demonstrated that innovation, productivity, and salaries are closely linked (Van Reenen, 2020).

Hypothesis 2: Effort Expectancy (EE) has a positive relationship with a positive attitude towards working with robots (At).

A good work environment is where the employees have the opportunity to develop all required competencies to work (Rose et al., 2013). It is supposed that if the answers are positive, the employee would be in a better position to achieve goals and the organization is adequate for robotization (Alias, 2018). Most probably, the management has shared the required information for understanding the context (or they suppose it would happen). Those respondents that are not actively employed, if the answer is positive, it is supposed that they recognize on themselves the required competencies to work or knowing how to work with robots.

Hypothesis 3: Social Influence (SI) has a positive relationship with a positive attitude towards working with robots (At).

Employees could prefer to work with robots maybe because important people around them, see positively to work with robots (Nguyen, 2022). In addition, it could be that they perceive gaining experience, social/personal recognition, or employability. The candidates in a selection process in front of two different companies, they may decide to join the company/work environment which is recommended by people whose opinions are valuable (Coldwell et al., 2008; Turban et al., 1998).

Hypothesis 4: Perceived Risk (PR) has a negative relationship with a positive attitude towards working with robots (At).

Robotization may generate the perception of an unsafe workplace, due to physical interaction with machines or because of the stress of job-automation risk (Jacob et al., 2023) and its related employment reduction (Acemoglu & Restrepo, 2019).

Hypothesis 5: Facilitating Conditions (FC) have a positive relationship with a positive attitude towards working with robots (At).

The employees may perceive as a good work environment where they have at their disposal all the required tools to perform with robots (Marler et al., 2006; Rose et al., 2013). It is supposed that if positive, the employee would have better chance to achieve goals and that management has shared all information and context required for such organizational transformation (Stata, 1989). It is quite similar in terms of implications than Effort Expectancy (Nahla Aljojo, 2020), but in this specific case it is referred to company factors (external to the individual) and not to personal capabilities.

Hypothesis 6: Positive emotions (PEm) have a positive relationship with a positive attitude towards working with robots (At).

People may feel attraction to work in a robotized environment and their attitude would be stronger and more proactive, mainly based on determination and enthusiasm (He et al, 2019).

Hypothesis 7: Negative Emotions (NEm) have a negative relationship with a positive attitude towards working with robots (At).

People may feel frustration and rejection to work in a robotized environment (Nomura et al., 2006) and their attitude would be weaker and less proactive in front of a crisis, mainly based on been hostile, upset, and distressed.

Hypothesis 8: Anxiety Emotions (AEm) have a positive relationship with a positive attitude towards working with robots (At).

Moderate levels of anxiety can serve to facilitate learning about the use of new tools, and even the acuity to adapt to new situations (Mora, 2009).

Hypothesis 9: Attitude (At) has a positive relationship with intention to work with robots (IU/RAW).

From an employee perspective, the use of robots may infer more job relevance (Kim, 2008). This could be related to the fact of being exposed to the state of the art in terms of technology, innovation, and efficiency (Kim, 2022). Attitude is essential to determine the acceptance of working with robots and to stay in the company (Coldwell et al., 2008; Fishbein & Ajzen, 1975).

3.3.4 Measurement scales

Once defined the constructs, it is necessary to confirm the measurement scales to be performed, which will allow us to know the way in which those constructs are related to the proposed hypotheses, as well as the possible connections among them.

Tay & Jebb (2016) consider that the scales are valid processes to distinguish behaviors, attitudes and personality traits that are not easily observable in organizations. In addition, their range of accuracy is much higher than other methodologies like a self-report, which are quite usual through new technologies (social networks, etc.). DeVellis, (2016) defends a similar approach about measurement scales, because provides mathematical consistency in the sense that a sample of more than 300 questionnaires is sufficient, to run an exploratory factor analysis of raw data, and validating potential results. Considering the relevance of an adequate measurement scale, there are two alternatives which provide consistency and validity to any study:

1) **To define our own and specific scale about the object of study**, which should be specifically validated. This alternative presents an initial challenge, because it is highly demanding in terms of workload and requires time. The positive aspect would be its fit with requirements and objectives of the study.
2) **Using a validated scale by previous research or studies**. This alternative offers absolute guarantee and would be fully accepted by academia.

For the development of data collection of this study, it has been prepared a questionnaire (50 questions) designed and adjusted to the constructs and areas to be investigated. The questionnaire has been validated by previous research (Dawes, 2008; Van Beuningen et al., 2012). Specifically in this case, it has been defined a Likert scale from 0 to 10 points for this dissertation. These types of scales, are widely accepted and contrasted for social sciences, allowing a very accurate attitudinal discrimination of participants. The scale allows eleven potential answers for each affirmative or negative sentence. Depending on its nature, the grading description has been differentiated: non-emotional grading is shown in Table 3.17; and emotional grading is shown in Table 3.18.

Table 3.17 Likert scale part I

	(Likert scale from 0 to 10)	
not at all	0 1 2 3 4 5 6 7 8 9 10	**fully agree**

Source: Own questionnaire

Table 3.18 Likert scale part II (emotions)

	(Likert scale from 0 to 10)	
you don't feel at all	0 1 2 3 4 5 6 7 8 9 10	**you feel it intensely**

Source: Own questionnaire

Each single observable variable has already been shown in the previous sub-chapter. Nevertheless, a merged version is available in table Table 3.19.

Table 3.19 Measurement scale part I

Constructs
Behavioral Intention to Use (BI)
BI1 Assuming I would have access to a robotized workplace, I would intend to work on it.
BI2 Assuming I would have access to a robotized workplace, I predict that I would work on it.
Attitude (At)
At1 Using robots in the workplace would be a good idea.
At2 Using robots in the workplace would be a wise move.
At3 Using robots in the workplace would be a step up.
At4 Using robots in the workplace would be an effective idea.
Performance Expectancy (PE)
PE1 I would consider useful to work with robots daily.
PE2 Working with robots would increase my chances of achieving important goals.
PE3 Working with robots would allow me to perform tasks more quickly.
PE4 Working with robots would increase my productivity.
Effort Expectancy (EE)
EE1 Learning to work with robots would be easy for me.
EE2 My interaction with the robot would be clear and understandable.
EE3 It would be easy to work with robots.
EE4 It would be easy for me to become skillful at working with robots.
Social Influence (SI)
SI1 People who are important to me, think I should work with robots
SI2 People who influence my behavior think I should work with robots
SI3 People whose opinions I value would prefer that I would work with robots
Perceived Risk (PR)
PR1 Working with robots is risky.
PR2 Would be too much uncertainty associated with working with robots.
PR3 Compared with other jobs, those with robots are riskier.
Facilitating Conditions (FC)
FC1 I would have the required resources to work with robots.
FC2 I would have the required knowledge to work with robots.
FC3 Robots would be compatible with the current systems and technologies that I am using.
FC4 In case of need, I would have support or assistance from others.

Source: Own questionnaire

Items are organized around each of the constructs, corresponding its Likert scale as indicated in Table 3.17. In addition, emotions are differentiated between positive, negative and anxiety, as already shown aggregated in Table 3.12. Likert scale for emotions have already been shown in Table 3.18. Both scales, depending on the grading, can show favorable, neutral, or unfavorable attitude towards working with robots.

3.3.5 Partial Least Squares – Structural Equation Modeling (PLS-SEM)

One of the main challenges of any scientific research, is to treat properly the data obtained in the field study.

The steps to follow are:

1. Delimitation of constructs, with their corresponding observable variables and the definition of scales, previously justified.
2. To establish different statistical methodologies, defining a correct path to follow in the treatment of raw data.

For this dissertation, it has been chosen a structural equation modeling (SEM). This model is a multivariate statistical technique that tests the estimation of causal relationships through statistical data. In addition, it establishes qualitative assumptions about causality. The precursor was Haavelmo (1943) and ten years later Simon (1953), developed the survey methodology. But it wasn't until 2000 when Pearl defined a formal model. Hair et al. (2011), state that the general Structural Equation Modeling has become a worldwide standard for study and research for cause-effect relationships between constructs. Being highly reliable to investigate topics related to management.

The SEM model is based on two statistical methods, one to know the relationships between different variables: Covariance-Based Model (CB-SEM); another based on Partial Least Squares (PLS-SEM). The literature on data processing reveals in the second case, that the implicit algorithm provides an overview of when it can be applied, in the most appropriate way, for the purpose of research.

If applied properly, it is a source of high statistical reliability to estimate causal models applied in multitude of theoretical models, assumptions, and empirical data situations (Haenlein & Kaplan, 2004), as the case in this dissertation.

In an ulterior paper, Hair, Hollingsworth, Randolph, and Chong (2017) distinguish between first-generation (cluster analysis, exploratory factor analysis, variance, regressions) and second-generation of multivariate methods (PLS) which suppose, not only the integration of primary techniques but a solid basis for studies in social sciences, marketing, etc.

According to Shmueli and Koppius (2011), explanatory models are those that try to test causal hypotheses to clarify “how” and “why” happens an empirical phenomenon. On the other hand, predictive models are applicable for definition and assessment of models which predict new or immediate observations, scenarios, and behaviors. According to these authors, the prediction capacity of a model, refers to generate predictions as much accurate as possible from just certain observations. This would apply as for cross-sectional studies as to longitudinal ones.

We understand that it is proven that our proposed model is the most successful for the empirical study of this dissertation. The phenomenon of increasing the presence of robots at work, still emerging since decades. It is true that there are already many related literatures detailed in this dissertation, but not as much linking robotization and its acceptance at work from a multi-industry and region level. We understand that the exploratory nature that defines the PLS-SEM model is the one which best fits our research to determine the level of acceptance of working with robots.

Hair et al. (2011) defines when the application of the PLS-SEM model may be ideal. Characteristics, which apply to the present research:

a) The use of the model is advisable when an exploration character of a certain construct or key ideas is intended. The prediction of acceptance behavior is a specific fact of how the model fits the research.

b) As an extension of a structural theory. Without any doubt, robotization at work is fully proven in this dissertation and is a global reality. Demonstrating that acceptance of robots at work is an extension of other theoretical reality, is what tries to demonstrate.

c) In those cases where the structural model is complex. This is the case of current research.

d) When the sample size is relatively low. Wong (2013) state that the PLS-SEM model has a high capacity to handle small sample sizes. Hoyle (1995) recommends samples of 100 to 200 in order to enhance results of the model and provide consistency for its analysis and evaluation, less than 100 would not provide a valid result. Despite we have enough sample to get conclusions, it is not a big size sampling (422). In addition, it is not necessary to assume a normal distribution of the data since it is a non-parametric model (Likert scale).

The SEM model has been widely used in recent years in many studies based on TAM technology acceptance models, as well as their extensions in Venkatesh and Davis (2000), Venkatesh and Bala (2008), Zhou (2011).

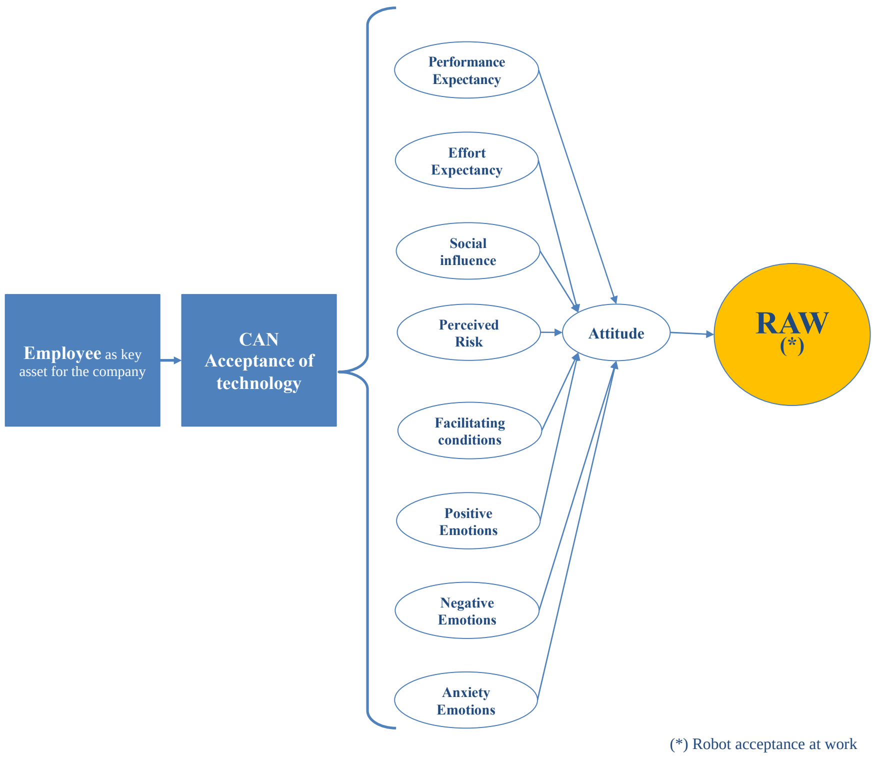
More specifically, the SEM model has also been applied in the area of leadership and organizational culture (Martínez Ávila & Fierro Moreno, 2018) as well as development of gamification with motivational purposes (Wee & Choong, 2019) and gamification for training (Rodríguez-López et al., 2021).

3.3.6 Estimated model

After having addressed the context, the objectives of this dissertation, as well as having analyzed applicable theoretical frameworks and formulated its hypotheses. Now it is time to show its graphical representation (Figure 3.6)

Our model shows the variables based on the CAN model, as precedents of the intention to work with robots (RAW). This block represents in a grouped way all our hypotheses. The employee (stakeholder) has a central and key position into the overall picture, represented through the **Robot Acceptance at Work**.

Figure 3.6 Applied model of Technology Acceptance



Source: Own development from Pelegrín et al., (2017).

In addition, it is essential to control specific variables that could alter our results (Kraemer & Thiemann, 1987; Binu Raj et al., 2022).

In that sense, it has been included six questions (Table 3.20) to understand better our results and to support additional conclusions. Below some introduction and context:

- **Have you previously worked with robots?** This question tries to differentiate among those participants that have already had a previous experience and those participants that have not had (or at least they do not recognize it). A previous exposure to a certain technology is recognized as a moderator of its acceptance (Kim, 2008).

- **In case you have already worked with robots, which has been your interaction or the mode?** At this point we can get an idea about the general distribution in terms of HRI. Assessing if certain types of previous interaction, may determine the level of technology (robot) acceptance. The participant could choose among different alternatives based on Scholz (2003).

- **In any case, which is the type of interaction, that you would prefer in case of interaction?** With this question, we will get an idea about the preferred Human-Robot interactions, as well as how the people would like to evolve in terms of HRI. In this case, the participant could choose among the same alternatives as the previous Scholz (2003), having add an additional option "*I would prefer not working with robots*". In this way we can determine, how many participants would like to stop interacting with robots, or even those participants that have not had any previous exposure to them, and they would like to still in that way. This item is relevant in the sense, that in a mandatory context as robotization, an employee might hold a negative attitude toward technology (Brown et al., 2002), but in the end he/she will work with robots because there is no other option. But with this specific question, we get to know what their preferences are, what is important for our study.

- **Your gender is…** As a demographic factor and determinant for the user-technology fit (Wang et al., 2020).

- **Year of birth**, considered as well as a demographic factor at individual-level (Wang, et al, 2020) This specific data has been useful to determine differences in the conclusions based on generations (Ng, E.S. et al., 2010). At the same time, had been useful to reject those participants below sixteen, based on criteria for this type of research (Eurobarometer). Generational analysis is a method that can offer crucial insights into comprehending public attitudes and actions (Alanen, 2009).
- Approximately, **how many years of professional experience do you have?** This question has allowed us to distinguish between more senior and entry level professionals. Even detecting those participants without any professional background, to understand better how future generation will approach the labor market in terms of robot's acceptance. The professional experience is relevant to be analysis, more even if there is previous exposure to such technology (Kim, 2008).

Table 3.20 Questionnaire about independent variables

Item	***Question***	***Answer***
3.1	Have you already worked with robots?	Yes No
3.2a	Your interaction with robots at work, has been as… (Scholtz, 2003)	Supervisory role. Operator interaction. Peer role. Mechanic role. Bystander role.
3.2b	If in the future you work with robots, you would like to play a... (Scholtz, 2003)	Supervisory role. Operator interaction. Peer role. Mechanic role. Bystander role. I would prefer not working with robots.
3.3	Gender (UTAUT2 Model)	Man Woman None of the above I prefer to do not answer
3.4	Year of birth	Numeric field (4 digits)

	(UTAUT2 Model) and grouped by generations (Boomers, Z, X, Y…)	
3.5	Years of working experience (approx.) (UTAUT2 Model)	Numeric field (2 digits without decimals)

Source: Own development.

CHAPTER 4. RESULTS

4.1 Unit of analysis

To the extent that there are a series of individual differences that moderate the effects of the different constructs presented, the questionnaire has been formulated with a series of questions that allows to stratify the results depending on previous interaction working with robots, type of that interaction, desired or preferred interaction with robots at work, gender, age, and years of professional experience.

It has been taken advantage of online questionnaires, as well as the international predoctoral stage in Japan (2019), together with personal and professional contacts, to get data from different sectors and regions.

4.2 Data gathering

The questionnaire has been defined in four languages: Spanish, English, Japanese and German, and published in Zoho Survey platform for 115 days from November 24th, 2022, until March 18th, 2023.

The target was to get between 300 and 500 participants, and for this reason, it has been reached a relevant number of potential participants (3000+), with the aim to receive around 20% minimum response (Chang & Taylor, 1999; Walters & Samiee, 1991).

In order to get as much participation as possible it has been distributed through social networks such as LinkedIn, Facebook, Instagram, and Twitter, reaching more than 3000 active professionals, being also distributed through university professors and students. In addition, it has been distributed through a series of entities like the Spanish Association of Managers of Social Responsibility (DIRSE), the Spanish Association for People Management (AEDIPE) and the Spanish Association of Robotics and Automation (AER), together with a series of companies and organizations (Table 4.1) especially related to robotization as for instance SEAT, Otaquest, Delaval, Istobal, H&T Presspart, Industrias Teixidó, Fintonic and Bossa Nova, which have already implemented or participated in relevant automation processes.

Table 4.1 Companies and institutions target for the questionnaire.

ABB	Fraunhofer IFF	PROXINNOV
AEDIPE	Goggo Network	Rethink Robotics (HAHN Group)
AER (Association of Rpobotics and Automation)	Goizper Group	RNB
Alstom	Gomtec	RoboHub
ARME Robótica Móvil	H&T Presspart	SANDVIK
Arrow Electronics	Helados Estiu	Sanitas
ASTI Technologies Group	Hilton Food Group	Sastre y Ferrer
Avaloq	IEEE Robotics and Automation Society	SEAT
AXELOS Global Best Practice	Industrias Teixido	Seismic
Bionic robotics	Institut de Robòtica i Informàtica Industrial CSIC-UPC	SICK sensor intelligence
Bossa Nova	Institute of Cognitive Sciences and Technologies (ISTC-CNR)	Sinterpack (soluciones paletizado)
CEMBRE	Institute of Intelligent Industrial Tech. & Systems for Advanced Manufacturing	SMS Group
Cibercotizantes	Instituto de Robótica para la Dependencia	STAM Mastering Excellence
CNRS	Iruña Tecnologías	StarShip
Delaval	Istobal	Starship Technologies
DIRSE	Jefo	Talentoo
Econocom	KUKA	Technische Universitatet Darmstadt
EKHI Etxeberria	LASCO	Telefónica
EURECAT	Marsi-Bionics / CSIC	UNIVERSAL ROBOTS
FANUC	New Scale Robotics	Laboratory for Manufacturing Systems and Automation (LMS)
Fintonic	OCADO Technologies	VECNA robotics
Flow robotics	Otaquest	Vicarios Surgical
Forética (Jobs 2030)	OUSTER	Vicosystems
Foro de Gobernanza de Internet en España IGF	PAL ROBOTICS	Webasto
Franunhofer IWU	PILZ	YASKAWA

Source: Own development based on research and personal contacts.

For instance, let's take the case of Delaval, a global company within the Tetra Laval Group. It was particularly intriguing to propose their participation in the study on a worldwide scale, with the idea that they could help disseminate the study extensively among their clients and stakeholders. We also reached out to other organizations like SEAT and manufacturers of robots, with the intention of involving them in distributing the survey among their stakeholders.

However, considering the final number of respondents, it appears that organizations have exhibited some reluctance in conducting surveys of this nature among their employees. This reluctance seems to stem from a desire to prevent any potential misunderstandings or concerns, as discussions about robotization often give rise to the notion of job reductions. At least, this is the feedback we received from certain companies.

An essential part of any empirical research is the method for collecting data, and because of that, the questionnaire has been translated into four languages, despite in German it has only gotten one complete answer (25 individuals went into the questionnaire without fulfilling nor one single question). Previously, questionnaires have been checked by scientists in academia and business professionals in Human Resources field (Haire et al., 1966; Sirota & Greenwood, 1971; Ronen & Kraut, 1977). Details of the survey are described in Table 4.2.

Table 4.2 Technical details of the study

Data gathering	Questionnaire	Comments/details
SAMPLING	Universe	Individuals over 18 years old located in any country.
	Invitations sent: • Companies and organizations indicated in Table 4.1. • Students and teachers in University (Master and Degree). • HR Directors of multinational/local companies. • Personal contacts. • Clients of Zima Consulting.	Difficult to be determined, but there is an estimation of having been addressed to 3.275 people.
	Distribution of questionnaires:	Have been addressed in different ways: IN TERMS OF CONTENT: • Each language depending on the direct participant. • When addressed to international associations or global companies, the email showed the link to each specific language to get higher participation rate. IN TERMS OF TOOLS: • Customized/individual email. • WhatsApp. • LinkedIn message. • Twitter/Instagram/Facebook/Messenger. • Introduced during University lectures.
	Sampling method	Convenience sample, but it has intentionally address to robotized companies and associations linked to Robotics, as well.
Field survey	Period	Almost 4 months, from November 24th, 2022, until March 18th, 2023.
	Data collection	Self-administered online survey "Zoho Survey platform". Accessible through computer, tablet, and smartphone.
	Received answers	461 314 in Spanish 96 in English 49 in Japanese 2 in German
	Absent/partial or atypical patterns	Partial: 39
	Total valid answers:	422

Source: Own development.

It is really complex to determine the universe of the sample, since it has been distributed through various channels, and there is also no record of who has responded or if for instance, they have shared it with third parties. What has been tried is to focus as much as possible on organizations and individuals with a certain relationship with the work environment and specifically technified environments (Table 4.1).

The survey was structured as a mandatory response format for all its questions, meaning that respondents couldn't proceed unless they answered the preceding question. Despite the comprehensive nature of this research, some questions were omitted, and the number of items was kept to a minimum to avoid making the survey overly lengthy for participants. In fact, it was designed to be completed in less than 5 minutes. However, 39 responses (8.5%) had to be excluded as they were incomplete.

Following an initial analysis of the gathered data, it can be concluded that no unusual or outlier data was present in the responses, except for 9 specific answers related to section 3.5 (years of working experience). These 9 responses were found to be inconsistent and were replaced by their mode to maintain consistency in this particular factor. Apart from these exceptions, all responses, excluding the 39 partial ones mentioned earlier, should be regarded as valid.

As part of an ulterior validation, in terms of composite validity, have been discharged the observables variables of negative emotion 1 (*distressed*); negative emotion 9 (*alert*) and anxiety emotion 2 (*attentive*). This elimination has been due to a CR>0.7.

4.3 Descriptive analysis

To gain a deeper comprehension of the survey data, it is essential to conduct a descriptive analysis, followed by a subsequent examination of statistical patterns.

4.3.1 Sociodemographic elements

Regarding **gender**, the distribution among the participants (Table 4.3), just over half are men (52.6%), having obtained a participation of 40.8% of women, so it is quite balanced. Likewise, it should be noted that more than 5% preferred not to indicate their gender and just over 1% did not identify with neither the masculine nor feminine gender. The distribution obtained is not significant to discard or questioning results, since the difference between men and women is not so as much significant, and even this difference can be considered as consistent, having in mind that according to International Labour Organization (2023), there is a difference of 25% between women and men, in terms of global labour force, reaching in some regions up to 50%.

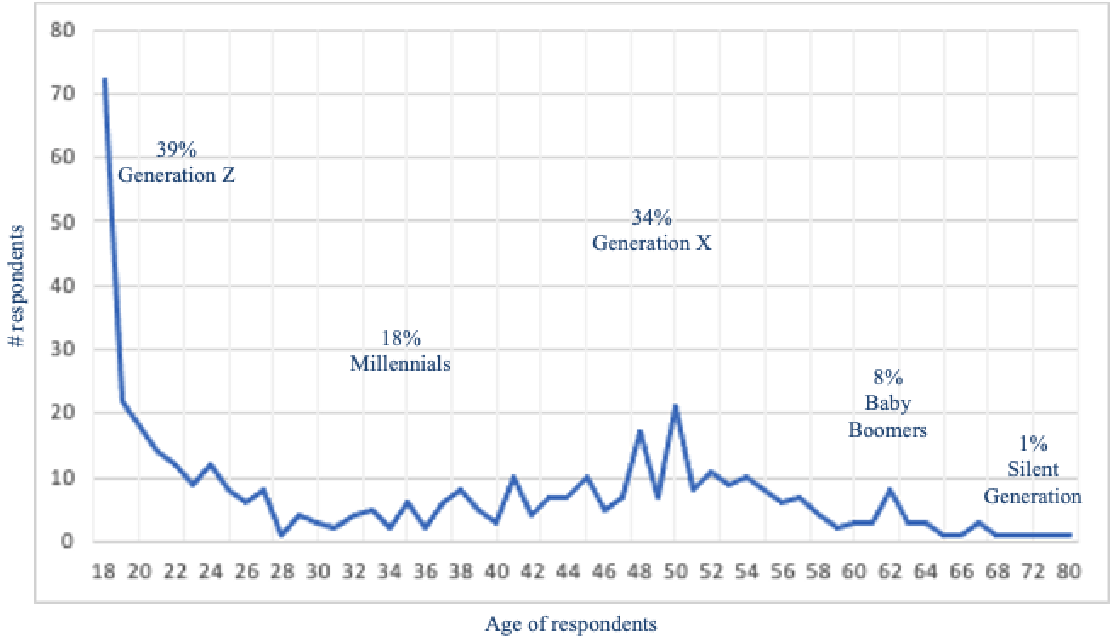
Table 4.3 Gender of participants

	frequency	%	% valid	Accumulative %
Man	222	52,6%	52,6%	52,6%
Women	172	40,8%	40,8%	93,4%
None of the above	5	1,2%	1,2%	94,5%
I prefer not to answer	23	5,5%	5,5%	100%
TOTAL	**422**			

Source: Own research

Regarding **age**, the participants span from 18 to 80 years, with an average age of 36 years and a mode of 18. This modal value is primarily attributed to the substantial participation of university students pursuing bachelor's and master's degrees. The standard deviation (SD) for this specific factor is 16, which contributes to the overall data, as depicted in the following representation (Figure 4.1):

Figure 4.1 Distribution of respondents by age



Source: Own development

More than half of participants (Millennials and Generation X) are in the most active stage of their professional career path.

An additional question introduced in the questionnaire pertained to the **number of years of work experience**. This question was included to evaluate the potential exposure of participants to robots in their work environment, as well as to discern variations in perceptions of robotics based on work seniority. After scrutinizing 422 responses related to this factor, we identified 9 responses that displayed inconsistencies, with data that did not align with the respondents' ages (indicating an excessive number of years of experience for their age group). To rectify this inconsistency, those 9 values out of 422 have been substituted with 0, which is equivalent to the mode of this factor. This adjustment was made because, considering their youth (ages 18-20), it would not be appropriate to replace their responses with the average value of 14.

To summarize the descriptive analysis of this factor: the average is 14, the mode becomes 0 due to the participation of students, and the standard deviation is 13.

More than half of the population have between 13 and 35 years of experience, what means that they bring a relevant knowledge and experience at work, together with a certain exposure to technological changes during these past years or even decades (computers, internet, emails, mobiles, office software, ERP, industrial automations, etc.).

In order to facilitate its understanding, the different number of years have been grouped and named (Table 4.4), depending on career development and stage of the professional life (from newcomers until retirement).

Table 4.4 Number of years of experience

	Grouped by years of experience	**# participants**	**% participants**	**Accumulative %**
No experience	0	72	17.06%	17%
Junior	From 1 to 3	88	20.85%	38%
Mid	From 4 to 7	39	9.24%	47%
Mid Senior	From 8 to 12	19	4.50%	52%
Senior	From 13-18	37	8.77%	60%
Mature	From 19-25	79	18.72%	79%
Close to retirement	From 25 to 35	65	15.40%	95%
Retired or close to retirement	From 36 to 40	13	3.08%	98%
Retired	More than 40	10	2.37%	100%
Total		**422**		

Source: Own research.

4.3.2 Factors and qualitative variables

Despite the predominantly quantitative nature of the questionnaire, certain questions have been included to allow for a more qualitative analysis. One of these aspects refers to previous experience in working with robots (Table 4.5). In the current sample, almost 30% reported having previous experience with robots. Regarding the remaining 70% that haven't had prior exposure to robots, it is probable that in reality, the percentage is even lower, because some individuals may interact with robots in their work without realizing it (e.g., through cash dispensers, algorithms, etc.…). To mitigate the potential misunderstanding caused by this, the questionnaire's introduction included an explanation of the concept of robot in the following manner:

"Robots adopt very different forms, being able to help or execute tasks without human intervention in whole or in part. For example, in the industry it is usually an articulated robot, while in the administrative field, the robot can be a computer program that performs both social and management tasks, replacing and/or helping people. In the present study we refer to all types of robots".

Table 4.5 Previous experience with robots at work

	frequency	%
NO	296[34]	70.1%
YES	126	29.9%
TOTAL	422	100%

Source: Own research

Another qualitative factor would be the **language** used by respondents (Table 4.6). As stated above, the questionnaire was run in four different languages, this circumstance can provide at a certain point, some context from a culture or idiosyncrasy perspective of respondents, mainly in the case of Japanese and Spanish, because the

[34] According to raw data, this frequency was initially 319, but 26 of these respondents, instead of marking "I have not worked with robots", they answered to the next question, assuming a previous specific type of interaction with robots. For this reason, these 26 respondents have been moved from "NO" into "YES". At the same time, in the opposite sense, 3 of the "YES" respondents indicated that their interaction was "I have not worked with robots", thus final adjustment (net) was summing 23 respondents to YES and deducting the same amount from NO.

participation in German is almost null and English respondents come from different regions as United States and the whole EU. Taking advantage of this information, some variables could be split between languages to explore potential finding.

Table 4.6 Participants by language

	Frequency	%
English	90	21%
German	1	0%
Japanese	41	10%
Spanish	290	69%
TOTAL	**422**	**100%**

Source: Own research

Furthermore, two additional questions were incorporated concerning the nature of interactions with robots. Firstly, if the respondent had prior experience working with robots, they were asked to specify the **type of Human-Robot Interaction** (HRI) they have had (Table 4.7). Upon examining the collected data, it becomes evident that the sample is reasonably well-balanced and reflective of the prevailing state of robotization in developed countries, which is generally characterized by a progressive rather than full implementation of robots in various environments. For instance, the role of "supervisory" had the lowest representation among current or past roles (9.5%), while the roles of "bystander" (32.5%) and "operator" (28.6%) were the most prevalent, representing both more than half of the sample.

Table 4.7 Type of interaction with robots at work in previous experiences

	frequency	%
Bystander role	41	32.5%
Mechanic or programmer role	19	15.1%
Operator interaction	36	28.6%
Peer role	18	14.3%
Supervisory role	12	9.5%
TOTAL	**126**	**100%**

Source: Own research based on Scholtz, 2003.

Lastly, participants were inquired about the kind of **interaction they would prefer with robots** (Table 4.8). This follow-up question was addressed as well to those individuals who hadn't had prior experience with robots, ensuring a comprehensive understanding of the preferred mode of interaction with robots of the entire sample.

Table 4.8 Type of desired interaction with robots at work

	frequency	%
Bystander role	34	8.1%
I would prefer not working with robots	43	10.2%
Mechanic or programmer role	51	12.1%
Operator interaction	72	17.1%
Peer role	98	23.2%
Supervisory role	124	29.4%
TOTAL	**422**	**100%**

Source: Own research based on Scholtz, 2003

Given that the basis of calculation (frequencies) for previous interactions with robots was 126, and for preferred types of interaction it was 422, we will evaluate these results in terms of the percentage variance between them. Upon making this comparison, it becomes evident that the supervisory and peer roles occupy the top positions in terms of preferences. These preferences can be rationalized by the fact that both roles entail a more "human" form of interaction, with the "peer" role emphasizing collaboration akin to a colleague, which contributes to enhanced performance and an attempt to imbue robots with a more human-like quality. Simultaneously, the supervisory role imparts a sense of control to the employee over the machine, rather than the reverse, as might be inferred from other forms of interaction, such as the "operator" role.

Although we will delve deeper into these aspects in the upcoming sections, it can be stated in advance that the "bystander" and "operator" interactions are less appealing compared to the current ones. Moreover, based on this sample, only 10% of respondents would opt not to work with robots.

After introducing the factors, it might be intriguing to combine some of them to gain a more comprehensive perspective and explore various facets of this data. Combining the level of seniority of participants with the type of the desired interaction (Table 4.9) brings some interesting information for contextualization.

On average for all professional/career stages, the supervisory and the peer role are the most attractive. On the contrary, the bystander interaction would be the less one.

Interestingly, when it comes to the appeal of working with robots in the workplace, the group that shows the highest degree of reluctance, in terms of percentages, is comprised of participants who lack prior experience with robots, despite being the youngest. This suggests that there may be a need for educational initiatives aimed at younger generations to mitigate their lack of familiarity with and fear of automation.

Table 4.9 Desire interaction depending on professional seniority

	Bystander role	I would prefer not working with robots	Mechanic or programmer role	Operator interaction	Peer role	Supervisory role	Total
No experience	11%	17%	21%	6%	21%	24%	100%
Junior	5%	11%	9%	18%	20%	36%	100%
Mid	3%	5%	20%	18%	23%	33%	100%
Mid-senior	10%	14%	14%	14%	29%	19%	100%
Senior	12%	9%	12%	9%	24%	35%	100%
Mature	12%	6%	6%	25%	23%	28%	100%
Close to retirement	8%	11%	11%	21%	26%	24%	100%
Retired or close to	0%	8%	0%	8%	38%	46%	100%
Retired	7%	7%	21%	21%	21%	21%	100%

Source: Own research based on Scholtz, 2003

To conclude with this specific factor related to HRI, we have already shown which type of interaction (if any) already had the participants (Table 4.7), as well as what kind of relationship with the robot the individuals would like to have (Table 4.8). From that point, participants have been grouped in terms of seniority at work as defined in Table 4.4. The purpose of this analysis is to show the difference between current or past situation, with a hypothetical desired interaction (Table 4.10 Previous HRI vs. Desired HRI (%) grouped by years of experienceTable 4.10). From this comparison, can be directly extracted that there is a clear improvement in terms of desire to work with robots. According to our data, this should be understood in the following terms: 70% of the participants had no previous experience with robots, but only 10% of the respondents would not like to work with robots (now or in the future). This means that there is a relevant % of participants that despite they have not worked before with robots, they would like to do so. At the same time, the “peer” and “supervisory” role improves significantly, especially for “juniors” and those “close to retirement”. This last aspect could be understood in the sense that very experience and senior professionals have a strong knowledge and experience in the job, thus consider that they could clearly assume that supervisory role towards a machine. For the youngest, it could be understood as a matter of professional aspiration.

Table 4.10 Previous HRI vs. Desired HRI (%) grouped by years of experience

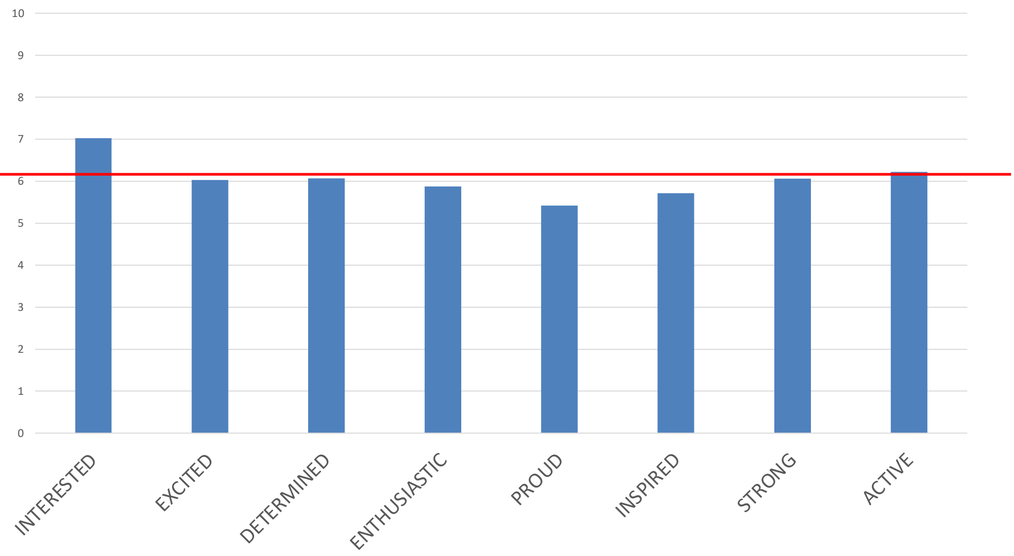
	Bystander role	Not working with robots	Mechanic or programmer role	Operator interaction	Peer role	Supervisory role
No experience	5%	-71%	21%	6%	16%	24%
Junior	-7%	-61%	7%	9%	16%	36%
Mid	-8%	-53%	10%	8%	20%	23%
Mid-senior	0%	-62%	10%	10%	24%	19%
Senior	0%	-56%	9%	0%	18%	29%
Mature	4%	-64%	2%	13%	19%	25%
Close to retirement	0%	-50%	-2%	9%	23%	20%
Retired or close to retirement	-15%	-54%	0%	0%	23%	46%
Retired	-14%	-57%	21%	14%	21%	14%

Source: Own research based on Scholtz, 2003

In addition to the data already reviewed, our questionnaire shows some items that correspond to the CAN Technology Acceptance Model, which brings attention towards emotions. Following the PANAS scale (Watson et al., 1998). This scale defines a serial of emotions that can be differentiated as "positive" detailed in Figure 4.2, "negative" (Figure 4.3) and "anxiety" shown in Figure 4.4.

Given the apprehension caused by robotization within certain segments of the population, especially in the context of workplace automation, it was anticipated that the highest emotional scores would not be associated with positive emotions. However, from the data obtained in current research, it has been confirmed that the highest rates are related to **positive emotions** (mean 6.07; SD 2.53 and mode 7).

Figure 4.2 Positive emotions (mean)



Source: Own research based on PANAS scale (Watson et al., 1998).

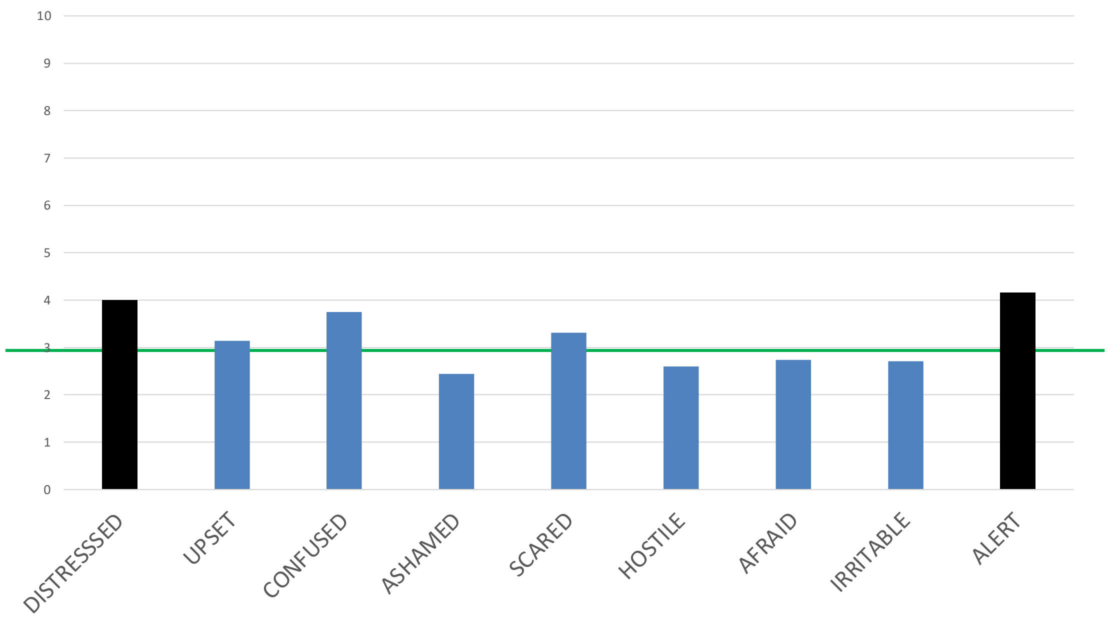
As previously described, the score is obtained from a Likert scale from 0 to 10, and the survey at this point (items from 2.1 to 2.8 -POS), tries to assess the positive emotions aroused by working with robots. The highest score is collected by "interested", which should be understood as a technology or tool that is part of the work environment and that generates interest and curiosity in its possible use or interaction.

Positive emotions represent the double compared to the negative, becoming quite balanced to the extent that only "interested" appears as the most valued, followed closely (6) by the rest (excited, determined, enthusiastic, inspired, strong and active), and only "proud" is slightly lower.

In relation to **negative emotions** (Figure 4.3), have been analyzed nine different emotions, but after the validation process of data, have discharged two of them (NEm1

Distressed and NEm9 Alert), because their reliability was below 0.7, and have been kept the seven remaining values (Chin, 1998), bringing a mean of 2.96; SD 2.52 and mode 0. This data represents almost half of the value compared to the positive ones, and only “Alert” and “Distressed” were a bit higher (around 4), what in fact is not relevant for current study as both have been excluded from the model due to their reliability.

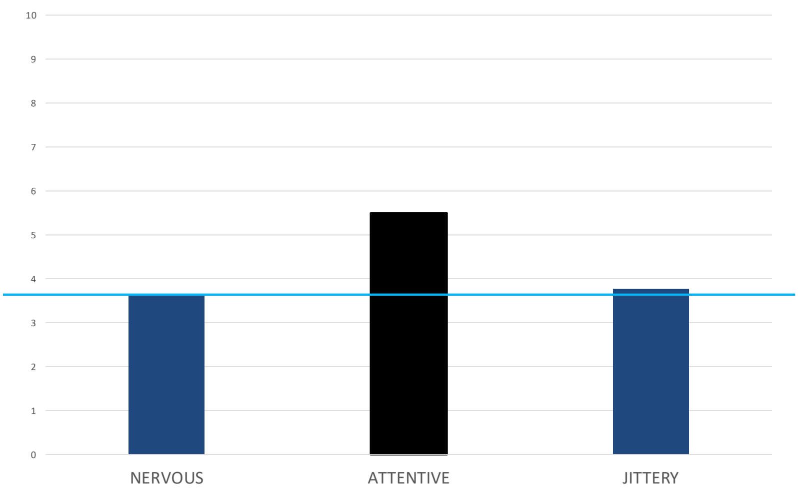
Figure 4.3 Negative emotions (mean)



Source: Own research based on PANAS scale (Watson et al., 1998).

In terms of **emotions linked to anxiety** (**Error! Reference source not found.**), they are ranked (mean 3.71; SD 2.65 and mode 0) in between positives and negatives. Clearly below the positives, and above the negatives. The item AEm2 "attentive" has been excluded from the model analysis because its reliability was below 0.7 and have been kept the two remaining values (Chin, 1998). All this analysis of our data can connect with the biological reaction that is acted in front of an unknown situation or a situation that can be considered at a certain point as dangerous (change of nature in the job, loss of employment or losing control of the work environment). In this type of situation, the cerebral cortex carries out an interpretation of this "danger" or challenge (Mora, 2009). In terms of robotization, we know that there are challenges in terms of knowing how to interact and use these robots, as well as challenges in terms of potential or effective organizational changes. In this sense, a certain (low) level of anxiety can even be positive to the extent that the brain activates the maximum capacities of the individual.

Figure 4.4 Anxiety emotions (mean)



Source: Own research based on PANAS scale (Watson et al., 1998).

In the survey have been considered as well other factors (Table 4.11) that will form the final analysis and conclusions. From these data, it can be observed that the item better valued is "Attitude" (7.56). For the rest, just to be mentioned that the "Social Influence" (5.10) and "Perceived Risk" (5.14) bring the lower rates, which could be understood in the context that despite there is a deep discussion in the general society about the convenience or not of automation at work, mainly due to the impact on employment, at the same time, robots at work could be not be perceived as risky at work from a physical/environment perspective, because safety at work in robotized organizations are usually higher (Badri Ahmadi et al., 2017).

Table 4.11 Average rating of other factors related to robotization at work

Factors	*Mean*	*SD*	*Mode*
Attitude (At)	**7.56**	**2.12**	**9.5**
Performance Expectancy (PE)	**7.34**	**2.32**	**10**
Effort Expectancy (EE)	**6.49**	**2.23**	**7**
Social Influence (SI)	**5.10**	**2.46**	**5**
Perceived Risk (PR)	**5.14**	**2.62**	**5**
Facilitating Conditions (FC)	**6.5**	**2.26**	**6.5**

Source: Own research

4.3.3 Conclusions of the descriptive analysis

Following the qualitative analysis of the research data, we highlight the most significant findings below:

The study involved a sample of 422 participants, comprising 296 individuals (70%) who reported no prior interaction with robots at work and 126 participants (30%) who have had such interactions. Regarding the nature of previous interactions with robots, the types of human-robot interactions were quite evenly distributed among those with experience. However, upon examining the desired type of interaction for the entire sample, a distinct preference emerged for the "peer" and "supervisory" roles.

Given that only 10% of the sample expressed disinterest in working with robots, it can be inferred that a significant portion of those who haven't previously interacted with robots (70%), are now interested.

The gender distribution within the sample can be characterized as fairly balanced, with a slightly higher presence of males compared to females (53% vs. 41%). This alignment closely mirrors the current global workforce distribution.

In terms of years of work experience (professional exposure), the average is 14 years, indicating a well-dispersed range that spans across different generations, including newer professionals, highly experienced individuals, and even retirees. This last aspect is particularly important to consider as the retirement age is progressively increasing and is expected to continue this trend. In terms of nationality or region of origin, 69% are Spanish speakers, being most of them from Spain, 10% from Japan, and the remaining 21% from different countries in Europe and United States.

The results on positive emotions are almost double (mean) that the negative ones (6.07 vs. 2.96). This may be due to the fact that robotization can arouse a certain interest and individuals can feel a certain attraction for technology and advantages in terms of effectiveness and goals achievement, but it seems that the feeling of “proud” despite is higher (5) than all the negative ones, does not stand out significant.

The presence of negative emotions, including anxiety, is still within acceptable limits. If anxiety levels were to rise significantly, surpassing positive emotions, it might suggest a potential risk of stress or individual and even organizational conflicts. However, in this particular study, although negative emotions are present, notably "anxiety," they still remain lower than positive emotions.

Regarding other factors linked to Robot Acceptance at Work, as per the CAN Technology Acceptance Model, it's worth noting that both "attitude" and "performance expectancy" exhibit highly favorable ratings, scoring above 7. In contrast, "social influence" and "perceived risk" have significantly lower ratings, with means approaching

5 and a relatively high standard deviation exceeding 2. The relatively low value (5.14) for "perceived risk" is actually a positive indicator in this specific research.

4.4 Statistical methodology for testing hypothesis

In this study, we have conducted a sequential statistical analysis process to assess all the hypotheses that were formulated within the model. To achieve this, we have undertaken the following phases:

PHASE 1. Exploratory factor analysis.

An Exploratory Factor Analysis of the main components through the Varimax rotation has been carried out in order to determine potential dimensions on the scales.

PHASE 2. Analysis of the measurement model.

Subsequently, the scales have been analyzed in terms of reliability, convergent validity, as well as discriminant validity of the measurement scales. In this second phase, has been eliminated the items: NEG1 (distressed), NEG9 (alert) and ANX2 (attentive) because of their low reliability (<0.7).

PHASE 3. Analysis of the structural model.

Finally, we have applied the R2, Q2, path coefficients, and assessed the significance level within the explanatory model for Robot Acceptance at Work. We employed the Consistent Partial Least-Squares Equation Modeling (PLSc-SEM) method, chosen for its reduced susceptibility to both type I and type II errors (Dijkstra & Henseler, 2015). This methodology is particularly recommended when data deviate from a normal distribution or when researchers cannot be entirely certain that it conforms to such a distribution.

The utilization of PLS-SEM has been discarded due to its tendency to elevate factor weights, leading to an underestimation of regression (Gefen et al., 2011). Nevertheless, it's crucial to note that PLSc-SEM should be employed exclusively in models where all constructs are reflective, which is the case here.

The chosen software for this testing and analysis was SmartPLS as it is less sensitive to the violation of assumptions of data normality (Chin, 1998; Ram et al., 2014).

4.5 Assessment of the measurement model

According to Hair et al. (2013), the requirement referred to the individual reliability of each observable variable has been verified. Specifically, the standardized loads of the observable variables must be greater than 0.7.

In this regard, the standardized loads of each item of the scales used are shown in the Table 4.12. In order to analyze this validity, it has been used Fornell & Larcker's criteria (Fornell & Larcker, 1981; Hair et al., 2017).

As already mentioned, some of the variables have been eliminated because were lower than the value reference of 0.7. This was the case of NEm1 (distressed); NEm9 (alert) and AEm2 (Attentive).

Having decided to eliminate these variables and keeping the rest under their specific factor, since the limit 0.7 for standardized loads is a flexible rule Chin (1998), particularly when the indicators contribute to the validity of content. The numbers on the diagonal (in **bold**) are the square root of the convergent validity (AVE see Table 4.13). Consequently, we can confirm the reliability of the constructs used in the model (Hair et al., 2011).

Table 4.12 Discriminant validity

	AEm	AT	EE	FC	IU	NEm	PR	PE	PEm	SI
Anxiety Emotions	**0.908**									
Attitude	-0.242	**0.901**								
Effort Expectancy	-0.283	0.568	**0.903**							
Facilitatiing Conditions	-0.249	0.519	0.676	**0.776**						
Intention to Use	-0.228	0.707	0.537	0.448	**0.958**					
Negative Emotions	0.736	-0.354	-0.387	-0.262	-0.344	**0.830**				
Perceived Risk	0.381	-0.292	-0.221	-0.117	-0.237	0.465	**0.859**			
Performance Expectancy	-0.208	0.828	0.590	0.539	0.653	-0.316	-0.259	**0.864**		
Positive Emotions	-0.191	0.713	0.563	0.560	0.569	-0.287	-0.179	0.714	**0.851**	
Social Influence	-0.080	0.510	0.492	0.439	0.411	-0.119	-0.053	0.558	0.594	**0.952**

Source: Own research based on Fornell-Larcker (1981).

In Table 4.13 are shown results for Cronbach's' alpha and composite reliability. Both references had to be greater than 0.7. Regarding the convergent validity in all constructs, the AVE is higher than 0.5, which is the minimum required.

Table 4.13 Composite reliability, Cronbach's alpha, and convergent validity (AVE)

Construct	CR > 0.7	CA > 0.7	AVE >0.5
Robot Acceptance at Work			
Anxiety Emotions	0.787	0.787	0.824
Attitude	0.923	0.922	0.811
Effort Expectancy	0.931	0.925	0.816
Facilitating Conditions	0.865	0.789	0.602
Intention to Use	0.911	0.910	0.918
Negative Emotions	0.929	0.925	0.689
Perceived Risk	0.847	0.824	0.738
Performance Expectancy	0.892	0.887	0.746
Positive Emotions	0.951	0.946	0.725

Social Influence	0.955	0.949	0.907

Source: Own research

4.6 Assessment of the structural model

To evaluate the significance of the path coefficients of the structural model, bootstrap has been used with 5,000 resamples (Hair et al., 2011). In bold, are reflected those significant explanatory variables.

Table 4.14 shows the results of the model, indicating the effects of each explanatory variable towards *Attitude* (At), as well as the *Attitude* towards the *intention to work with robots* (IU/RAW). Through the PLS predictive test, have been calculated R^2 and Q^2. The results show a model with high predictive capacity regarding *Attitude* and reasonable towards the *intention to work with robots* (IU/RAW).

The R^2 value of the endogenous variable *Attitude* is 77.6%. At the same time, according to Hair et al., 2011 (pp:145), when Q^2 is greater than zero indicates that exogenous constructs have relevance in predicting the endogenous variable of the model. These results allow us to affirm that the goodness of fit is adequate, and the model predicts the *intention to work with robots*.

Table 4.14 Path coefficients and p-values

	R^2	Q^2	Path coefficient	p-values
	0.727	0.714		
Performance Expectancy -> Attitude			0.600	**<0.001**
Effort Expectancy -> Attitude			0.038	0.418
Social Influence -> Attitude			0.006	0.859
Perceived Risk -> Attitude			-0.063	**0.029**
Facilitating Conditions -> Attitude			0.024	0.567

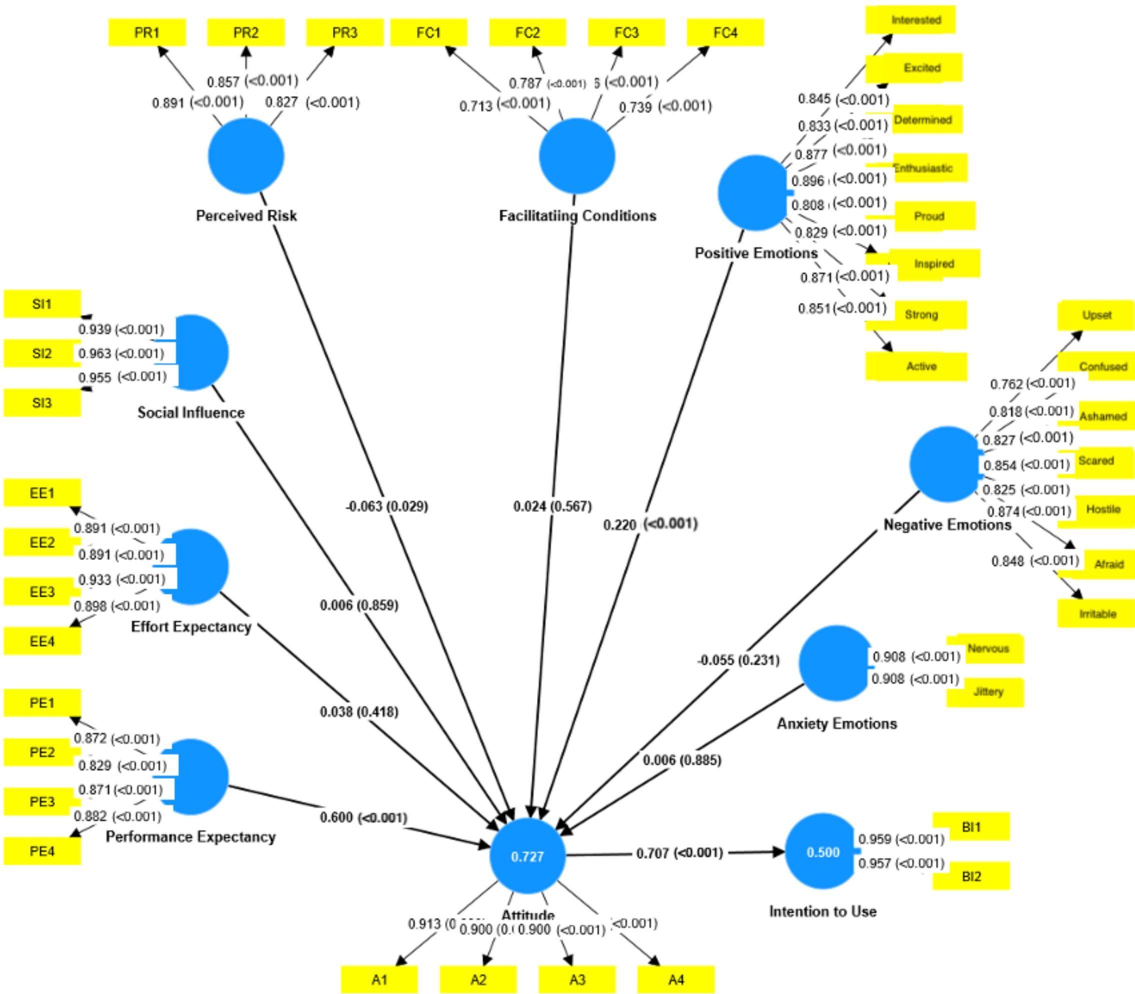
Positive Emotions -> Attitude			0.220	**<0.001**
Anxiety Emotions -> Attitude			0.006	0.885
Negative Emotions -> Attitude			-0.055	0.231
	0.500	0.453		
Attitude -> Intention to Use			0.707	**<0.001**

Source: Own research

In addition, having revised the p-values, we can confirm that *Performance Expectancy*, *Perceived Risk* and *Positive Emotions* have an obvious influence towards *Attitude*. Likewise, *Attitude* also has a clear influence towards the *intention to work with robots* (IU / RAW).

Below a graphical representation (Figure 4.5) of the entire structural model, showing Path coefficients, p-values and R^2. Afterwards, this assessment will be translated into some specific conclusions regarding the formulated hypothesis.

Figure 4.5 Structural model results: Path coefficient, p-values and R^2



Source: Own development

All exogenous variables -grouped- (*Performance Expectancy; Effort Expectancy; Social Influence; Perceived Risk; Facilitating Conditions; Positive Emotions; Negative Emotions and Emotions based on Anxiety*) have predictive capacity (72.7%) towards *Attitude*.

4.7 Hypothesis testing

In this sense, as stated before, *Performance Expectancy* has specific influence towards *Attitude*, hence H1 is accepted .

In the same way, *Perceived Risk* also has influence towards *Attitude*, so the H4 has been accepted as well, same as H6 because *Positive Emotions* has a p-value <0.001, therefore it shows a clear influence towards *Attitude*.

Attitude influences and has predictive capacity towards the *intention to work with robots* (IU/ RAW), explaining 50% of the variance in this intention, hence H9 is accepted.

Although all exogenous variables together have predictive capacity and influence, separately not all of them, show enough influence towards *Attitude*. In fact, *Effort Expectancy, Social Influence, Facilitating Conditions, Emotions based on Anxiety and Negative Emotions* show a p-value >0.05, thus H2, H3, H5, H6, H7 and H8 have not been accepted.

The conclusions regarding the acceptance of the introduced hypothesis are presented in Table 4.15, based on results obtained.

Table 4.15 Summary of hypothesis testing

Hypothesis 1	Performance Expectancy (PE) has a positive relationship with a positive attitude towards working with robots (At).	**ACCEPTED**
Hypothesis 2	Effort Expectancy (EE) has a positive relationship with a positive attitude towards working with robots (At).	**REJECTED**
Hypothesis 3	Social Influence (SI) has a positive relationship with a positive attitude towards working with robots (At).	**REJECTED**
Hypothesis 4	Perceived Risk (PR) has a negative relationship with a positive attitude towards working with robots (At).	**ACCEPTED**
Hypothesis 5	Facilitating Conditions (FC) have a positive relationship with a positive attitude towards working with robots (At).	**REJECTED**
Hypothesis 6	Positive Emotions (PEm) have a positive relationship with a positive attitude towards working with robots (At).	**ACCEPTED**
Hypothesis 7	Negative Emotions (NEm) have a negative relationship with a positive attitude towards working with robots (At).	**REJECTED**
Hypothesis 8	Anxiety Emotions (AEm) have a positive relationship with a positive attitude towards working with robots (At).	**REJECTED**
Hypothesis 9	Attitude (At) has a positive relationship with intention to work with robots (IU/RAW)	**ACCEPTED**

Source: Own development

CHAPTER 5. CONCLUSIONS

5.1 General conclusions from the research

Considering the outcomes that have confirmed the acceptance or rejection of the proposed hypotheses and summarizing the research conducted in this doctoral dissertation, we can categorize the most significant findings into three main sections:

Theoretical contributions. This doctoral dissertation consists of an initial section that offers a comprehensive examination of the components involved in robotization. To begin, it conducts a comprehensive overview of the concept itself. It acknowledges that automation technology has been in development for over six decades and has been implemented across various industries, employing diverse approaches and methods. Furthermore, it sets the foundational framework and background necessary for comprehending the nature of robots and the methods of engaging with them. It also makes a clear distinction between the advantageous and societal merits of robotics on one hand, and the unfavorable or contentious facets such as potential risks, conflicts, ethical quandaries, and philosophical contemplations associated with robotics on the other. Subsequently, it delves into the primary ramifications and the extent to which this technology is embraced by employees, companies, and society at large.

Focusing mainly on employees, have been analyzed the implications of robotization in the work environment (Kim, Sehoon) and its acceptance by employees (Çiğdem, Paluch, Venkatesh) and more specifically its impact on the workplace (Knod, Wall), innovation in the organization (Tomatzky, Wang) as well as the perception of the performance of the individual and the company (Goodhue, Moravec, Robinette, Rust, Wall).

This research contributes to a field that has piqued considerable interest among practitioners but has received relatively scant attention within the academic literature. It involves a comprehensive examination of the acceptance of robots across various industries and without geographical limitations. The study delves into the diverse forms of automation and robotization present in different sectors, encompassing artificial intelligence, integrated algorithms in work processes, industrial automation, software applications, autonomous devices, drones, robotics for rescue operations, weaponry, agricultural monitoring and analysis systems, tractors, wearable technology applied in work environments, and more. Each of these specific applications carries distinct implications depending on the nature of the job, the country, and, of course, the individual involved. This research considered all these variables, along with factors like performance and effort expectancy, facilitating conditions, risk perception, social influence, and emotions, to provide a comprehensive context for understanding how employees perceive and accept robots in the workplace. Furthermore, an examination has been conducted to ascertain the anticipated or preferred form of Human-Robot Interaction (HRI) that employees would prefer. Part of this analysis has been categorized in accordance with Scholtz's framework (2003) and yields a positive outcome, indicating that a majority of new entrants into current robotized job market (87%) show a desire to work alongside robots. Furthermore, it confirms that performance expectations and positive emotions are positively correlated with a positive attitude towards working with robots, thus impacting positively the intention to work with them. On the contrary, the perceived risk from the employee, has a negative influence on that intention.

Methodological Contributions. The research methodology is based on the CAN (Cognitive-Affective Normative) model by Pelegrín-Borondo et al. (2017), which is a derivative of TAM2 (Venkatesh & Davis, 2000) and UTAUT2 (Venkatesh et al., 2012). This model has been validated through various recent investigations in the realm of acceptance of technological products and services.

A notable enhancement lies in the development of a scale that goes beyond, than merely incorporating the assumptions derived from the previously mentioned models. This scale also integrates an emotions questionnaire (PANAS scale by Watson et al., 1988), aligning with the normative and cognitive aspects of technology acceptance models.

The statistical analysis conducted validates the utilization of this scale with a diverse sample of 422 individuals hailing from Europe, Japan, North Africa, and the United States. This diversity adds a valuable dimension to the research. Furthermore, the sample exhibits enriching characteristics, such as a wide age range spanning from 18 to 80 years, as well as diversity across industries, job roles, and prior experiences with human-robot interaction. Including these heterogeneous criteria in the sample for a specific topic like the acceptance of robots in the workplace mitigates the potential bias that could arise from factors like the level of industrialization or robotization in a particular industry or country, or the disparity between employees with managerial versus operational responsibilities. By avoiding a narrow focus on a single country or a specific subset of participants, such as only targeting German employees or just production plant operators, the data collected remains more robust and representative for a general overview of the topic. In any case, natural distinctions have been performed, as for instance regarding the age of participants. As shown in Figure 4.1, it has been organized depending on generations instead of merely age. This distribution could bring valuable input aligned with the current internal discussions in the companies as well as in academia about how different generations influence on organizational and managerial aspects (Joshi et al., 2011; Ng et al., 2010).

Conclusions and hypotheses of the model: The model put forward nine research hypotheses, of which four have been accepted, while five have been rejected, as determined by the PLSc-SEM statistical analysis. Notably, the variable "attitude (At)" holds influence and demonstrates a robust predictive capacity on the intention to use and its equivalent in this research, the robot acceptance at work (IU - RAW). As previously emphasized, it stands out with remarkable explanatory power when considering the model as a whole. In essence, the perception of competent performance in automation processes (performance expectations) significantly bolsters the intention to collaborate with robots. In simpler terms, the research has established that individuals who anticipate high performance levels at work are inclined to collaborate with robots because they anticipate superior performance outcomes. This could encompass immediate performance improvements and rewards, as well as the development of skills to effectively work with robots, ultimately enhancing their employability.

Furthermore, a second influential factor with strong predictive and explanatory capabilities are the positive emotions (PosE), with a particular focus on the enthusiasm generated by working alongside robots. This encompasses the excitement associated with engaging with cutting-edge technology (state of the art) and the impetus to act, all of which emerge as prominent results. Another factor that has an impact on employees' inclination to work with robots is the perceived risk, as anticipated. In this case, the factor demonstrates a negative correlation with a favorable attitude toward robotization. A more detailed examination of each formulated hypothesis and the outcomes obtained is provided in the following paragraphs.

HYPOTHESIS 1. ACCEPTED. Performance Expectancy (PE) has a positive relationship with a positive attitude towards working with robots (At).

In other words, when individuals anticipate that working with robots will enhance their performance or productivity, they are more likely to have a positive attitude toward collaborating with robots. This attitude encompasses their willingness, comfort, and enthusiasm in engaging with robotic technology as part of their job. All the statistical examinations conducted confirm the acceptance of the proposed hypothesis. In all instances, the intention to use is contingent upon the perception of performance, which is notably the most prominent variable. The central emphasis revolves around performance and the benefits associated with working alongside robots. Clearly, if the system functions effectively and delivers the anticipated performance, it will be embraced by individuals seeking economic incentives or salary advancements, professional growth, recognition or simply the opportunity to enhance their technological skills. All these implications may have their base in aspects like the fact that the expectation of an improved performance is often driven by the perception that robots can carry out tasks more accurately, quickly, or efficiently than humans. At the same time, there is confidence in robot assistance, what generates a more positive attitude, as the employee trust that working alongside robots will lead to better outcomes. This conception helps and support the Human-Robot interaction. This increase in terms of efficacy and efficiency, may generate the idea for the employee, that workload is reduced giving a chance to focus on more meaningful tasks, alleviating concerns about monotonous or repetitive work. All these circumstances may justify a greater job satisfaction, and consequently a positive attitude towards working with robots, as our H1 states.

HYPOTHESIS 2. REJECTED. Effort Expectancy (EE) has a positive relationship with a positive attitude towards working with robots (At).

The perception of how much effort or difficulty is associated with working with robots is not linked to having a more positive disposition toward working alongside them.

The hypothesis showing relatively low acceptance indicators within the model, suggests that the aptitude and capacity to work with robots, or the ability to acquire such skills, does not exert a positive influence on an employee's inclination to collaborate with robots. In brief, the ease with which they can adapt to working with robots does not boost their intention to do so. And this can be due because the effort can always be perceived as a barrier, because it implies that working with robots may complicate their work processes or require additional learning and adaptation. This additional learning and adaptation can be linked to the use of robots, or because the tasks change bringing more complexity. This additional complexity can reduce their comfort and enthusiasm because they may anticipate a steep learning curve or extensive training.

In summary, the absence of a positive relationship between Effort Expectancy (EE) and a positive attitude towards working with robots (At) can be due to the fact that when employees anticipate that using robots will be challenging, cumbersome, or complex, it tends to diminish their enthusiasm and willingness to embrace robot technology in their work. The perceived effort becomes a barrier to cultivating a positive attitude toward robot collaboration or interaction.

HYPOTHESIS 3. REJECTED. Social Influence (SI) has a positive relationship with a positive Attitude towards working with robots (At).

The influence of social factors, such as the opinions or attitudes of others, does not appear to significantly impact or improve the positive disposition individuals have toward collaborating with robots in the workplace.

In contrast to prior studies examining the acceptance of products or services like mobile phones, social networks, or video games, where the role of social influence is highly significant, and sometimes even decisive, this research does not identify social influence as a prominent factor. Social influence does not hold the power to significantly impact the intention to work in a robotic environment. In summary, the decision to collaborate with robots or not is primarily made by the employee, irrespective of the opinions or influences of others or their social circles. This can be supported because Attitudes towards working with robots may be more intrinsically formed based on personal experiences, beliefs, and perceptions rather than being heavily influenced by external social factors. Individuals might have their own unique reasons and motivations for embracing or resisting robot collaboration. At the same time, as explained before, robotization may imply changes in terms of tasks, responsibilities and autonomy and the decision to work with robots will be often closely tied to job roles and those responsibilities. In that sense, social influence may have limited impact here, as employees may have their own agendas, prioritizing their professional needs and objectives over social or family's pressures.

HYPOTHESIS 4. ACCEPTED. Perceived Risk (PR) has a negative relationship with a positive attitude towards working with robots (At).

This inverse relationship between perceived risk and a positive inclination to work with robots can be attributed to several underlying factors. Firstly, it may stem from the fear of potential job displacement, where employees worry that robots could supplant their positions, resulting in a loss of job security and income. Additionally, there are more personal reasons, such as a lack of familiarity with robots. Many individuals have limited exposure to working alongside robots, leading to unfamiliarity and uncertainty, which can foster mistrust and apprehension, but our data has not brought any (positive nor negative) correlation between prior exposure to robots at work and the perceived risk. To address this issue, our questionnaire included a query as well, about prior experiences in terms of human-robot interaction. As well as “desired” type of HRI. Furthermore, this perception of risk can be intertwined with a sense of loss of control, which manifests as a diminishing sense of autonomy and job satisfaction, as it implies a shift toward less fulfilling tasks. From a physical perspective, safety concerns regarding accidents or errors involving robots also contribute to this perception, despite studies demonstrate that robotized environments tend to be safer for employees in terms of accidents.

The ramifications of this context around risk perception can be profound. It often translates into increased resistance to change, as employees who perceive elevated levels of risk are more likely to resist the adoption of robotic technologies in the workplace. This resistance can obstruct the implementation of automation and impede organizational progress. Simultaneously, a heightened sense of risk can lead to diminished job satisfaction, eroding morale among employees, and potentially resulting in reduced productivity and engagement. These apprehensive attitudes towards robots can also lead to missed opportunities for employees, including skill development and career advancement, especially in an era marked by increasing automation.

Furthermore, organizations that neglect to address these negative perceptions of robotics among their employees may lag behind competitors who effectively integrate automation into their operations. This, in turn, can result in increased costs associated with implementing training and support programs to counteract resistance and alleviate perceived risks, representing an additional financial burden for organizations.

HYPOTHESIS 5. REJECTED. Facilitating conditions (FC) have a positive relationship with a positive attitude towards working with robots (At).

This means that the presence or availability of favorable conditions, resources, or support systems that could make easier to work with robots does not necessarily results in a more positive disposition toward robot collaboration at work. This may happen because even when facilitating conditions are present, individuals may value their autonomy and decision-making capacity in the workplace. This is a reason which was already introduced. Employees may want to decide independently whether or not to work with robots, rather than feeling compelled by external or facilitating factors. At the same time, individuals are unique, and attitudes towards working with robots can vary widely among individuals. While facilitating conditions might make it easier for some to adopt robot technology, others may still have personal preferences, experiences, or reservations that influence their attitudes differently. At the same time, employees may have varying levels of technical proficiency and comfort with robotic technology. Facilitating conditions alone may not address individual differences in technical readiness or willingness to adapt. What means that similar facilitating conditions do not bring similar attitude towards RAW, because even intrinsic motivations and job satisfaction would influence on the perceived benefits of robot collaboration. In summary, the absence of a positive relationship between Facilitating Conditions (FC) and a positive Attitude towards working with robots (RAW) suggests that, in the context of robotic technology adoption, personal preferences, intrinsic motivations, technical proficiency, and individual autonomy play significant roles in shaping attitudes. While facilitating conditions can provide valuable resources and support, they may not be the sole determinants of a positive attitude toward robot collaboration. Individuals' unique experiences and perspectives also influence employee’s attitude.

HYPOTHESIS 6. ACCEPTED. Positive Emotions (PEm) have a positive relationship with a positive attitude towards working with robots (At).

When individuals experience positive emotions in the context of their interactions with robots or while using robotic technology in the workplace, they are more likely to have a positive attitude toward collaborating with robots.

Positive emotions like interest, enthusiasm, inspiration or proud can enhance an individual's comfort and enthusiasm when working with robots. These emotions can create a more relaxed and enjoyable experience, leading to a more favorable attitude, contributing to overall job satisfaction. When employees feel positive about their work, they are more likely to have a positive disposition toward technological changes, being open to new experiences, changes and new ways of working, including incorporating robotic technology into their routines. In addition, when employees have positive emotions, they feel more motivated and engaged, thus more likely to approach challenges and changes with a positive mindset. In summary, the positive relationship between Positive Emotions (PEm) and a positive Attitude towards working with robots (At) is rooted in the impact of positive emotions on comfort, enthusiasm, job satisfaction, openness to adaptation, motivation, and the quality of HRI.

HYPOTHESIS 7. REJECTED. Negative Emotions (NEm) have a negative relationship with a positive attitude towards working with robots (At.).

According to our results, the presence of negative emotions or feelings in the context of interactions with robots or while using robotic technology in the workplace does not necessarily lead to a less favorable attitude toward working with robots. These negative emotions do not inherently undermine a positive attitude. In general terms, individuals can experience a mix of emotions in response to situations. While negative emotions may occur, they do not necessarily dominate or dictate the overall attitude. In that sense, our positive emotions and other factors like performance expectancy (efficiency, productivity, or task simplification), can counterbalance some negative emotions. At the same time, the relationship between emotions and attitudes can be influenced by specific contexts (ages, stages, countries…), and negative emotions can sometimes serve as adaptive responses to challenges. For example, initial frustration during the usual learning curve of working with a new technology (like in this case, robots) may lead to improved proficiency and, eventually, positive experiences. In the same way, individuals may weigh the potential benefits of robot collaboration against any negative emotions they experience. And one individual and psychological aspect, is based on the fact that some individuals have emotional resilience and the ability to manage negative emotions effectively. They may view negative emotions as temporary hurdles to overcome rather than as determinants of their overall attitude.

HYPOTHESIS 8. REJECTED. Anxiety Emotions (AEm) have a positive relationship with a positive attitude towards working with robots (At).

When individuals experience anxiety-related emotions in the context of their interactions with robots or while using robotic technology at work, it typically does not lead to a more positive attitude toward working with robots. Instead, anxiety emotions tend to be associated with a less favorable or hesitant RAW. The main problem arises because anxiety emotions often stem from concerns about one's ability to perform tasks effectively. When employees feel anxious about working with robots, they may worry about making mistakes or encountering difficulties, leading to a less favorable attitude. Of course, the natural fear of the unknown, something new or unfamiliar, such as robotic technology can lead to anxiety and a less positive attitude. Anxiety emotions can lead to discomfort and a sense of unease. In the context of robot collaboration, this discomfort can translate into a less favorable attitude due to the perceived stress associated with working with robots, making individuals hesitant. They may resist change and prefer to stick with familiar environments, methods and routines. And linked to our H4, anxiety emotions can also be tied to the perception of risk or potential negative outcomes. If individuals associate robot interactions with a high risk of errors or negative consequences, they are less likely to have a positive attitude.

HYPOTHESIS 9. ACCEPTED. Attitude (At) has a positive relationship with intention to work with robots (IU/RAW).

When employees hold a favorable attitude toward working with robots, they are more likely to express the intention to work with robots in their job tasks. A positive attitude contributes to a greater willingness and openness to work with robots, rooted in the favorable disposition individuals have toward robot technology. This disposition aligns with an openness to change, intrinsic motivation, perceived benefits, reduced resistance, and enhanced job satisfaction, all of which contribute to their intention to actively engage with robotization at work.

A positive attitude toward working with robots indicates that individuals have a favorable view of automation, robot technology and their potential benefits. This positive disposition often aligns with an intention to explore and utilize robots in their job roles. Considering that this positive attitude tends to be more open to change and innovation in the workplace. They are willing to adapt to new technologies and explore how robots can enhance their job performance.

Furthermore, a favorable attitude is frequently linked to intrinsic motivation and job satisfaction, where individuals derive contentment and fulfillment from their professional roles. This intrinsic motivation can serve as a catalyst for the desire to collaborate with robots, as employees perceive it as a way to enhance their job satisfaction, boost efficiency, alleviate their workload, or enhance task precision (performance expectation). This perspective also diminishes resistance to technological shifts. When individuals maintain a positive outlook on robotic technology, they are less inclined to oppose its assimilation into their work procedures, thus nurturing the inclination to work alongside robots.

5.2 Final conclusions. Implications for theory and future research

To conclude this dissertation, we intend to create a final section that consolidates concluding thoughts on the results, and research directions recommended for exploring technological acceptance, the processes of robotization, and implications for organizations.

This doctoral dissertation provides a comprehensive examination of literature encompassing robotization, technology acceptance, and management, spanning from a contextual understanding to operational and strategic viewpoints. It encompasses a practitioner-oriented approach while also delving into the most relevant academic insights in the field. After scrutinizing the model and using it as a fundamental component for hypothesis testing, it becomes apparent that, due to the absence of direct influence from effort expectancy, social influence, facilitating conditions, negative emotions, and emotions linked to anxiety, it's plausible to consider that these factors, when considered individually, do not wield substantial influence.

In fact, the process of robotization is often an imposed reality for employees, and, in many cases, they have limited autonomy in the matter. It might be reasonable to assume that an individual's attitude toward working with robots is shaped in a somewhat nebulous manner, with only a few variables playing a significant role. However, this dissertation has effectively demonstrated that the collective impact of performance expectancy, perceived risk, and positive emotions shapes employee’s attitude and, consequently, influences the intention to work with robots.

In addition, this research expected to highlight differences between regions, that for sure may support future research. The German input has been discharged from Table 5.1 because of its low relevance in terms of participation.

Table 5.1 Factor's results by region

	Behavioral Intention to Use	Attitude	Performance Expectancy	Effort Expectancy	Social Influence	Perceived Risk	Facilitating Conditions	Positive Emotions	Negative Emotions	Anxiety Emotions
	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean
Spanish	7,98	7,62	7,41	6,70	5,21	5,22	6,71	6,05	3,03	3,91
English	7,28	7,44	7,28	6,40	4,68	4,80	6,29	6,26	2,76	3,61
Japanese	7,55	7,51	7,10	5,26	5,33	5,33	5,46	5,84	2,84	2,57
Overall	**7,78**	**7,56**	**7,34**	**6,49**	**5,10**	**5,14**	**6,50**	**6,07**	**2,96**	**3,71**

Source: Own development

After this previous contextualization, we will address the questions already formulated in chapter 1, as part of the objectives for this dissertation:

- Do employees recognize the exposure to robotics as an employability advantage? As per the performance expectancy factor, it is reasonable to understand that employees assume that robotization increase their capabilities in terms of performance. In addition, considering the different types of interaction and the preferences shown in our research, shown in Table 5.2, most of the participants (87%) without previous exposure to robots at work, would like to work with them and more than a half in a peer or supervisory role. In fact, in most of the cases the employees would repeat the type of interaction they had in the past, except in the case of "bystander role", that only 13% of participants would repeat. What is relevant in this specific slot, is that they would not like to still with that interaction, because 53% of them, would prefer a peer or supervisory role. This data shows that employees consider that interaction with robots is positive and consequently beneficial for employment. Otherwise, participants had chosen "no future interaction with robots" as preference for their future.

Table 5.2 Current HRI vs. desired HRI depending on current role

		To desired role						
		Bystander role	Not working with robots	Mechanic or programmer role	Operator interaction	peer role	Supervirsor role	
From Current role	Bystander role	15%	7%	5%	10%	29%	34%	**100%**
	Not working with robots	9%	13%	10%	16%	22%	31%	**100%**
	Mechanic or programmer role	5%	0%	58%	21%	5%	11%	**100%**
	Operator interaction	3%	6%	11%	39%	25%	17%	**100%**
	peer role	0%	0%	6%	11%	61%	22%	**100%**
	Supervirsor role	0%	0%	33%	0%	8%	58%	**100%**

Source: Own development

- Does robotization have a positive influence on the workplace? Given that performance expectancy exhibits a positive correlation with a favorable attitude toward working with robots, it suggests that its existence is advantageous, contributing to enhanced performance, including efficiency, productivity, workplace safety and accuracy. In addition, results obtained show that there some positive emotions generated around working with robots, like interest, activeness, excitement and enthusiasm, often rated at 7 or higher. And these emotions contribute to a better climate at work.
- Is robotization perceived (by employees) as a tool for improving (their) performance? Aligned with our findings, the employees consider that robotization impacts positively on their performance. Furthermore, considering a managerial perspective and incorporating insights from our research results and revised literature, there are some aspects that deserve to be highlighted:

In the realm of human-robot interaction, extending beyond mere physical engagement, it's crucial to highlight that organizations need to execute the implementation of robotization, particularly when it's integrated into decision-making processes, with great care. The deployment of such conceptually and intellectually intricate systems must be meticulously crafted to yield advantages for all individuals and stakeholders. Failure to do so could lead to unforeseen repercussions, particularly when artificial intelligence and deep learning are integrated into the framework. Management should strive to steer clear of potentially critical consequences.

- Which factors may determine robot acceptance at work? According to our results, the performance expectancy from the employee and positive emotions, together with minimum negative emotions. Some additional reflections and recommendations are shared on this regard:

As per Moravec (1999), forecast for working schedules suggests a significant reduction in the number of working hours for humans, with a simultaneous increase in the presence of robots. Hence, it becomes imperative that robots and artificial intelligence serve the interests of people, rather than the other way around. After analyzing our own data, relevant literature, and conducting a comprehensive review spanning decades, it's evident that there is a natural resistance to workplace robotization. In line with one of the goals of this research, the following recommendations for organizations are included to help overcome this innate resistance among individuals. It's important to note that expecting complete "change acceptance" may not be realistic. Nevertheless, these recommendations can aid in fostering a more human-centric environment aligned with the Industry 5.0, as robotization should create additional daily opportunities for employees. In this context, it's valuable to emphasize certain principles and guidelines for a more efficient implementation from an organizational standpoint:

Employees should have a **clear understanding of what robotization entails**, its mechanics, and the potential impact it can have on their work and daily lives. This understanding should extend to address the principles and prerequisites related to confidentiality and privacy for all parties involved. It's crucial to acknowledge that, in many instances, an extensive volume of data will be generated and handled (due to comprehensive recording), and it's imperative to establish trust regarding its handling while complying with all the stipulations outlined in the New European Data Protection Regulation or relevant regulations applicable depending on each geographical region. This clarity will contribute to a better comprehension of performance expectations, effort demands, and potential risks. It will also foster positive emotions related to trust while diminishing the impact of negative social influences or disruptions, along with negative emotions, including anxiety-related emotions.

Employees and stakeholders, which may encompass prospective customers, should also possess the capability to comprehend how any robotization or automation process contributes to or facilitates decision-making and how humans oversee and manage the suggestions and actions executed by the machine. In essence, it's not solely about elucidating the functioning of the machine but, more importantly, about elucidating **how employees collaborate with the outcomes and functions produced by the**

machine. This approach supports any negative social influence against the robotization process.

Early comprehensive communication towards stakeholders: To the extent possible, initiate team involvement and communication promptly by connecting ongoing efforts to a clear future vision. This not only allows individuals time to ponder and embrace forthcoming organizational transformations but also provides the employees with the opportunity to attentively listen to, understand, and address apprehensions throughout the robotization process. This step should be executed as soon as possible.

Similar to the importance of employees "**unlearning**" to rid themselves of false beliefs, limitations, or harmful habits, the "managerial robotization process" should also be open to unlearning certain predefined aspects to safeguard against undesirable inclinations or results. Management should acknowledge that everything can be redefined if necessary. Humans (management) should exhibit and demonstrate greater adaptability than machines. In fact, one of the main challenges that we face as society, is about how are we going to teach and develop to the new generations to fit better with this unforeseeable future and environment.

Developing and training on the necessary skills for this emerging environment, in accordance with the principles of avoiding discrimination and promoting gender equality, initiating targeted and specialized training and educational initiatives that align with market and innovation trends. Such an endeavor would have a favorable effect on reducing anxiety, negative emotions, and the expectations of effort.

Providing a **risk evaluation** and adopting a proactive approach to risk management, as for example, the anxiety and apprehension stemming from the introduction of new technologies in the workplace have given rise to technophobia, and employees feel a sense of susceptibility. This vulnerability isn't solely related to potential job loss but also extends to concerns about data privacy (as already mentioned) and even physical aspects like workplace health and safety. Evaluating the potential challenges and intricacies of the change management strategy allows Management, to anticipate and prepare for them. Any robotization initiative may even gain greater commitment if risks are identified early and effectively addressed. In this context, in the same way that employees perceive risks, it is advisable for organizations to similarly assess potential risks to counter any apprehensions or misunderstandings if necessary.

Recognize and incentivize behaviors and actions that support robotization, ensuring they align with overarching corporate values, behaviors, and reward systems to prevent any ambiguity and miscommunication. This approach would contribute positively to the performance expectation of the employees.

As a concluding remark before addressing the limitations, it's worth noting that this research may introduce novel perspectives, enriching the literature on business automation and employer branding. It does so by providing valuable insights into employees' perceptions, particularly by examining the impact of robotization, with a particular focus on a three-fold perspective: workplace implications, the perception of innovation at work, and individual performance.

As reflections and future research, not only as a result of this dissertation, but also because of the dedication for five years to the study of the acceptance of robots at work, these additional points are presented:

For future research and to lay the foundation for more extensive and in-depth contemplation, it's essential to recognize that our society is shifting from a paradigm where machines aided people to a new, already emerging model in which humans might support machines, because machines have not full human capabilities, yet.

To make progress within the evolving framework of Industry 5.0, it could be valuable to investigate, *how decisive could be the leadership style and hierarchies on the robot acceptance at work*, and based on different rational dimensions, understand potential implications of this RAW on stakeholders' perceptions.

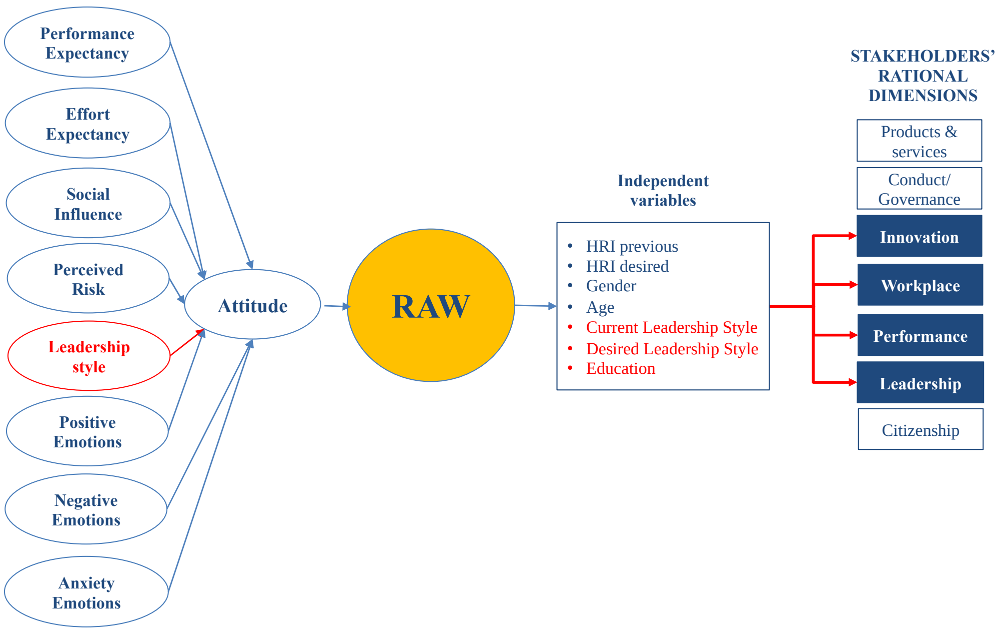
For that purpose, as shown in Based on these results, additional analysis could be carried out in order to better understand the implications that robotization and its acceptance by employees may have on the perception of stakeholders on aspects such as innovation, workplace, organizational performance and leadership as such.

Figure 5.1, the factor of facilitating conditions (FC) which appeared in our original model, it has been replaced by leadership style. This alteration is grounded in the findings from our research regarding this factor (FC) and is supported by the idea that the leadership style can be recognized as a condition that could facilitate the adoption of technology in the workplace. This change might enhance the model's relevance, particularly due to its improved alignment with the specific proposed domain (workplace).

In addition, some independent variables would be included to provide additional input in order to determine the most convenient leadership style depending on HRI, personal factors and level of education of employees.

Based on these results, additional analysis could be carried out in order to better understand the implications that robotization and its acceptance by employees may have on the perception of stakeholders on aspects such as innovation, workplace, organizational performance and leadership as such.

Figure 5.1 Future research



Source: Own development

5.3 Limitations

The Technology Acceptance Models offers numerous advantages. It has undergone extensive testing across various technologies, and many researchers have made references to it. However, a notable criticism is that it has often been used in studies without practical applications within companies and institutions (Ajibade, 2018). It's important to note that this study was not conducted within a specific company, under the implementation of a particular robotization project, or exclusively within a single industry. While the absence of direct "application" can be acknowledged, the questionnaire items, the depth of theoretical and contextual analysis, and the wide-ranging participation from various educational backgrounds, geographical locations, industries, job functions, gender, and age groups contribute valuable insights to our research. This broad scope enhances the significance of our study as a high-level exploration in this field. In addition, to minimize as much as possible the limitations of the models, it has been specifically decided to use the CAN model because it provides a more complete vision, including contextual and emotional factors that are so valuable for the topic at hand.

Furthermore, a disparity between attitude and the intention to use in mandatory settings has been identified in previous studies (Brown et al., 2002; Hwang et al., 2016). It's important to note that even when the decision to implement robotization is made by the company and is initially mandatory for the employees, there are circumstances where employees might resist or hinder such implementation. This resistance could manifest through activities by labor unions, strikes, or simply a lack of engagement and motivation at work. Additionally, employees have the option to resign and seek employment in a company that has not adopted such robotization.

Another aspect that has come as a surprise after closing the questionnaire is the limited participation in the German language section. Only one survey was completed, despite several other German participants starting but not finishing the questionnaire. It's essential to emphasize that the study's conclusions remain unaffected, and the results should not be called into question due to this low level of German participation. The overall participation in other languages such as Spanish, Japanese, or English has been quite representative both individually and in aggregate. It's worth noting that a significant portion of the questionnaires completed in English were filled out by German speakers. In this regard, it's possible that the target audience for the German survey (German corporations involved in robotization) may have found the questionnaire either too extensive or not sufficiently focused on the most relevant issues for them at the time. Undoubtedly, this is an aspect to consider for future studies in this field.

Nonetheless, there are prospects for future research by conducting targeted studies within specific industry sectors to derive more specific conclusions. Furthermore, longitudinal studies could provide valuable insights into assessing the impact of specific strategies over time. However, the primary challenge in this regard is that technologies and automation intelligence are rapidly evolving, with new generations adopting different approaches that need to be integrated with the perspectives of more experienced professionals. This dynamic context makes it challenging to arrive at definitive conclusions with a fixed viewpoint. However, it also opens up numerous opportunities for future research and analysis.

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CHAPTER 7. ANNEXES

Annex 1 Simulation ChatGPT with key words

CHATGPT Artificial Intelligence’s response to the request of generating content based on the keywords of this dissertation: Robot acceptance at work; Human-robot interaction; Robotics; CAN Model.

Robot acceptance at work refers to the willingness of employees to work alongside robots in their workplace. It is an important aspect of human-robot interaction, which encompasses the ways in which humans and robots interact and cooperate in various settings.

The acceptance of robots at work can be influenced by a variety of factors, including the perceived usefulness and ease of use of the robots, the perceived risks associated with their use and the degree of control that employees have over the robots.

The CAN model, which stands for Compatibility, Ability, and Need, is a theoretical framework used to understand the acceptance of technology, including robots, in the workplace. According to the CAN model, individuals are more likely to accept a new technology if it is compatible with their work practices, if they have the ability to use it effectively, and if they perceive a need for it.

In the context of robotics, the CAN model can help organizations understand the factors that are likely to influence the acceptance of robots by their employees. By ensuring that robots are compatible with existing work practices, providing training to employees to improve their ability to use the robots, and highlighting the benefits of robot use to meet organizational needs, organizations can increase the likelihood of successful human-robot interaction and acceptance of robots in the workplace.

Source: Chat.openai.com (Retrieved on April 4th, 2023)

Annex 2 Introduction to questionnaire (English)

The present research tries to determine factors for the acceptance of robots at work.

Robots can adopt very different natures and appearances, being machines that can help or execute tasks in a totally or partially autonomous way, without requiring constant instruction or guidance. For example, in industry it usually corresponds to the image of an articulated robot, while in the administrative or business field, the robot surely has no physical representation, and may consist of software, algorithm or functionality that replaces tasks previously performed by a person. In this study we refer to all types of robots, both industrial, business, or administrative.

If you are currently working, answer the questions with your current position in mind. If you are a student, retired or unemployed, answer the questions considering your last job or the one you are preparing for.

To answer this questionnaire will take you approximately 5 minutes, read the questions carefully and grade your answer.

Responses are strictly confidential and anonymous. The answers will only be analyzed by the researcher. To resolve any questions or expand any type of information related to the study or the information contained in this document, you can send an email to juanandres.montero@urv.cat

If you are interested in receiving a summary with the conclusions of this study, please send an email to juanandres.montero@urv.cat and I would be pleased sending it to you.

Thanks in advance for your participation.

Annex 3 Questionnaire employee's acceptance (English)

Although your answers are completely anonymous, we ask your permission to treat them statistically together with the rest of the answers obtained.		**Yes ☐**	**No ☐**

1. Thinking that your company would incorporate robots, having a direct relationship with your work, indicate your opinion, from 0 not at all, to 10 fully agree:

Q	***Items***	**(Likert scale from 0 to 10)**
	Performance Expectancy (PE)	
1.1	PE1 I would consider useful to work with robots daily.	0 1 2 3 4 5 6 7 8 9 10
1.2	PE2 Working with robots would increase my chances of achieving important performances.	0 1 2 3 4 5 6 7 8 9 10
1.3	PE3 Working with robots would allow me to perform tasks more quickly.	0 1 2 3 4 5 6 7 8 9 10
1.4	PE4 Working with robots would increase my productivity.	0 1 2 3 4 5 6 7 8 9 10
	Effort Expectancy (EE)	
1.5	EE1 Learning to work with robots would be easy for me.	0 1 2 3 4 5 6 7 8 9 10
1.6	EE2 My interaction with robot would be clear and understandable.	0 1 2 3 4 5 6 7 8 9 10
1.7	EE3 It would be easy to work with robots.	0 1 2 3 4 5 6 7 8 9 10
1.8	EE4 It would be easy for me to become skillful at working with robots.	0 1 2 3 4 5 6 7 8 9 10
	Social Influence (SI)	
1.9	SI1 People who are important to me, think I should work with robots	0 1 2 3 4 5 6 7 8 9 10
1.10	SI2 People who influence my behavior think I should work with robots	0 1 2 3 4 5 6 7 8 9 10
1.11	SI3 People whose opinions I value, would prefer that I would work with robots	0 1 2 3 4 5 6 7 8 9 10
	Behavioral Intention to Use (BI)	
1.12	IU1 Assuming I have access to a robotized workplace, I intend would work on it.	0 1 2 3 4 5 6 7 8 9 10
1.13	IU2 In case I would have access to a robotized workplace, I predict that I would work on it.	0 1 2 3 4 5 6 7 8 9 10
	Attitude (At)	
1.14	At1 Using robots in the workplace would be a good idea.	0 1 2 3 4 5 6 7 8 9 10
1.15	At2 Using robots in the workplace would be a wise move.	0 1 2 3 4 5 6 7 8 9 10
1.16	At3 Using robots in the workplace would be a positive step.	0 1 2 3 4 5 6 7 8 9 10
1.17	At4 Using robots in the workplace would be an effective idea.	0 1 2 3 4 5 6 7 8 9 10
	Perceived Risk (PR)	
1.18	PR1 Working with robots is risky.	0 1 2 3 4 5 6 7 8 9 10
1.19	PR2 Would be too much uncertainty associated with working with robots.	0 1 2 3 4 5 6 7 8 9 10
1.20	PR3 Compared with other jobs, those with robots are riskier.	0 1 2 3 4 5 6 7 8 9 10
	Facilitating Conditions (FC)	
1.21	FC1 I would have those required resources to work with robots.	0 1 2 3 4 5 6 7 8 9 10
1.22	FC2 I would have the required knowledge to work with robots.	0 1 2 3 4 5 6 7 8 9 10
1.23	FC3 Robots would be compatible with current systems and technologies in the organization.	0 1 2 3 4 5 6 7 8 9 10
1.24	FC4 In case of need, I would have support or assistance from others.	0 1 2 3 4 5 6 7 8 9 10

2. Think about how you feel/felt about working with a robot, and value the following adjectives from 0 you don't feel at all, to 10 you feel it intensely:

Q	***Items***		**(Likert scale from 0 to 10)**
2.1	PEm1	Interested	0 1 2 3 4 5 6 7 8 9 10
2.2	PEm2	Excited	0 1 2 3 4 5 6 7 8 9 10
2.3	PEm3	Determined	0 1 2 3 4 5 6 7 8 9 10
2.4	PEm4	Enthusiastic	0 1 2 3 4 5 6 7 8 9 10
2.5	PEm5	Proud	0 1 2 3 4 5 6 7 8 9 10
2.6	PEm6	Inspired	0 1 2 3 4 5 6 7 8 9 10
2.7	PEm7	Strong	0 1 2 3 4 5 6 7 8 9 10
2.8	PEm8	Active	0 1 2 3 4 5 6 7 8 9 10
2.9	NEm1	Distressed	0 1 2 3 4 5 6 7 8 9 10
2.10	NEm2	Upset	0 1 2 3 4 5 6 7 8 9 10
2.11	NEm3	Confused	0 1 2 3 4 5 6 7 8 9 10
2.12	NEm4	Ashamed	0 1 2 3 4 5 6 7 8 9 10
2.13	NEm5	Scared	0 1 2 3 4 5 6 7 8 9 10
2.14	NEm6	Hostile	0 1 2 3 4 5 6 7 8 9 10
2.15	NEm7	Afraid	0 1 2 3 4 5 6 7 8 9 10
2.16	NEm8	Irritable	0 1 2 3 4 5 6 7 8 9 10
2.17	NEm9	Alert	0 1 2 3 4 5 6 7 8 9 10
2.18	AEm1	Nervous	0 1 2 3 4 5 6 7 8 9 10
2.19	AEm2	Attentive	0 1 2 3 4 5 6 7 8 9 10
2.20	AEm3	Jittery	0 1 2 3 4 5 6 7 8 9 10

Annex 4 Independent variables (English)

Q	Finally, some items that same as the overall questionnaire, will be treated anonymously.	
	Question	***Answer***
3.1	Have you already worked with robots?	• Yes • No
3.2a	Your interaction with robots at work, has been as… (Scholtz, 2003)	• Supervisory role. • Operator interaction. • Peer role. • Mechanic role. • Bystander role.
3.2b	If in the future you work with robots, you would like to play a...	• Supervisory role. • Operator interaction. • Peer role. • Mechanic role. • Bystander role. • I would prefer not working with robots.
3.3	Gender (UTAUT2 Model)	• Man • Woman • None of the above • I prefer to do not answer
3.4	Year of birth (UTAUT2 Model) and grouped by generations (Boomers, Z, X, Y…)	• Numeric field (4 digits)
3.5	Number of years' experience (UTAUT2 Model)	• Numeric field (2 digits without decimals)
We will be very grateful if you invite friends, colleagues, or family to participate in this survey. To do this, you should copy and paste the following link		www.enlace.com

Annex 5 Introduction to employee's acceptance questionnaire (Spanish)

La presente investigación consiste en analizar factores determinantes para la aceptación de los robots en el trabajo.

Los robots pueden adoptar naturalezas y apariencias muy diferentes, siendo máquinas que pueden ayudar o ejecutar tareas de manera total o parcialmente autónoma, sin requerir de instrucción o guía constante. Por ejemplo, en la industria suele corresponder con la imagen de un robot articulado, mientras que en el ámbito administrativo o de negocio, el robot seguramente no tiene representación física, pudiendo consistir en un software, algoritmo o una funcionalidad que reemplaza tareas que anteriormente realizaba una persona. En el presente estudio nos referimos a todo tipo de robots, tanto industriales, como de negocio o de administración.

Si en la actualidad está trabajando, responda a las preguntas pensando en su puesto actual. En caso de ser estudiante, jubilado o estar desempleado, responda a las preguntas considerando su último trabajo o aquel para el cual se está preparando.

Responder a este cuestionario le llevará aproximadamente 5 minutos, lea con atención las cuestiones y gradúe su respuesta.

Las respuestas son estrictamente confidenciales y anónimas. Las respuestas sólo serán analizadas por el investigador. Para resolver cualquier duda o ampliar cualquier tipo de información relacionada con el estudio, puede dirigir un correo electrónico a juanandres.montero@urv.cat

Se le agradece de antemano, su participación en este estudio.

Annex 6 Questionnaire employee's acceptance (Spanish)

A pesar de que sus respuestas son completamente anónimas, le pedimos permiso para tratarlas estadísticamente juntamente con el resto de las respuestas obtenidas.	Sí ☐	No ☐

1.- Pensando en que su empresa incorporara robots y tuvieran una relación directa con su trabajo, indique su opinión, desde 0 nada de acuerdo, hasta 10 totalmente de acuerdo:

Q	*Items*	(escala Likert de 0 a 10)
	Expectativa en desempeño (PE)	
1.1	PE1 Encontraría útil trabajar a diario con robots.	0 1 2 3 4 5 6 7 8 9 10
1.2	PE2 Trabajar con robots aumentaría mis posibilidades de conseguir desempeños importantes.	0 1 2 3 4 5 6 7 8 9 10
1.3	PE3 Trabajar con robots me permitiría realizar tareas más rápidamente.	0 1 2 3 4 5 6 7 8 9 10
1.4	PE4 Trabajar con robots aumentaría mi productividad.	0 1 2 3 4 5 6 7 8 9 10
	Expectativa de esfuerzo (EE)	
1.5	EE1 Aprender a trabajar con robots sería fácil para mí.	0 1 2 3 4 5 6 7 8 9 10
1.6	EE2 La interacción con el robot sería clara y entendible.	0 1 2 3 4 5 6 7 8 9 10
1.7	EE3 Encontraría fácil trabajar con el robot.	0 1 2 3 4 5 6 7 8 9 10
1.8	EE4 Me resultaría fácil tener las habilidades necesarias para trabajar con robots.	0 1 2 3 4 5 6 7 8 9 10
	Influencia Social (SI)	
1.9	SI1 Personas que son importantes para mí, piensan que debería trabajar con robots.	0 1 2 3 4 5 6 7 8 9 10
1.10	SI2 Personas que influyen en mi comportamiento, piensan que debería trabajar con robots.	0 1 2 3 4 5 6 7 8 9 10
1.11	SI3 Personas cuyas opiniones valoro, preferirán que yo trabaje con robots.	0 1 2 3 4 5 6 7 8 9 10
	Intención de uso (BI)	
1.12	IU1 Asumiendo que tendré acceso a los robots para trabajar, intentaré usarlos.	0 1 2 3 4 5 6 7 8 9 10
1.13	IU2 Asumiendo que tendré acceso a los robots para trabajar, predigo que los usaré.	0 1 2 3 4 5 6 7 8 9 10
	Actitud (At)	
1.14	At1 Utilizar robots para trabajar es una buena idea	0 1 2 3 4 5 6 7 8 9 10
1.15	At2 Utilizar robots para trabajar es aconsejable	0 1 2 3 4 5 6 7 8 9 10
1.16	At3 Utilizar robots para trabajar es avanzar	0 1 2 3 4 5 6 7 8 9 10
1.17	At4 Utilizar robots para trabajar es una idea eficaz	0 1 2 3 4 5 6 7 8 9 10
	Riesgo percibido (PR)	
1.18	RP1Trabajar con robots sería arriesgado.	0 1 2 3 4 5 6 7 8 9 10
1.19	RP2 Habría demasiada incertidumbre relacionada con el hecho de trabajar con robots.	0 1 2 3 4 5 6 7 8 9 10
1.20	RP3 Comparado con otros puestos, aquellos que son con robots serían más arriesgados.	0 1 2 3 4 5 6 7 8 9 10
	Condiciones facilitadoras (FC)	
1.21	FC1 Dispondría de los recursos necesarios para trabajar con robots.	0 1 2 3 4 5 6 7 8 9 10
1.22	FC2 Tendría el conocimiento necesario para trabajar con robots.	0 1 2 3 4 5 6 7 8 9 10
1.23	FC3 Trabajar con robots sería compatible con otras tecnologías que utilizo.	0 1 2 3 4 5 6 7 8 9 10
1.24	FC4 Si tuviera dificultades para trabajar con robots, podría obtener ayuda de otras personas.	0 1 2 3 4 5 6 7 8 9 10

2.- Piense en lo que siente sobre trabajar con un robot, y valore los siguientes adjetivos desde 0 no lo siente, a 10 lo siente intensamente:

Q	***Items***		**(a valorar escala Likert de 0 a 10)**
2.1	PEm1	Interesado	0 1 2 3 4 5 6 7 8 9 10
2.2	PEm2	Emocionado	0 1 2 3 4 5 6 7 8 9 10
2.3	PEm3	Convencido	0 1 2 3 4 5 6 7 8 9 10
2.4	PEm4	Entusiasmado	0 1 2 3 4 5 6 7 8 9 10
2.5	PEm5	Orgulloso	0 1 2 3 4 5 6 7 8 9 10
2.6	PEm6	Inspirado	0 1 2 3 4 5 6 7 8 9 10
2.7	PEm7	Decidido	0 1 2 3 4 5 6 7 8 9 10
2.8	PEm8	Activo	0 1 2 3 4 5 6 7 8 9 10
2.9	NEm1	Afligido	0 1 2 3 4 5 6 7 8 9 10
2.10	NEm2	Disgustado	0 1 2 3 4 5 6 7 8 9 10
2.11	NEm3	Confundido	0 1 2 3 4 5 6 7 8 9 10
2.12	NEm4	Apenado	0 1 2 3 4 5 6 7 8 9 10
2.13	NEm5	Asustado	0 1 2 3 4 5 6 7 8 9 10
2.14	NEm6	Hostil	0 1 2 3 4 5 6 7 8 9 10
2.15	NEm7	Atemorizado	0 1 2 3 4 5 6 7 8 9 10
2.16	NEm8	Irritable	0 1 2 3 4 5 6 7 8 9 10
2.17	NEm9	Vigilante	0 1 2 3 4 5 6 7 8 9 10
2.18	AEm1	Nervioso	0 1 2 3 4 5 6 7 8 9 10
2.19	AEm2	Estaría a la expectativa	0 1 2 3 4 5 6 7 8 9 10
2.20	AEm3	Inquieto	0 1 2 3 4 5 6 7 8 9 10

Annex 7 Independent variables (Spanish)

Q	**Para finalizar, cumplimente una serie de datos que por supuesto, serán tratados de forma anónima y confidencial.**	
	Pregunta	***Respuesta***
3.1	¿Ha trabajado ya con robots?	• Sí • No
3.2a	Si ha trabajado con robots, ha sido como...	• Supervisor o instructor del robot. • Operador del robot. • Compañero del robot (compartíamos tareas). • Mecánico o programador del robot. • Espectador. Lo veía, pero no interactuaba nada.
3.2b	Si en un futuro trabajara con robots, le gustaría...	• Supervisar o ser instructor del robot. • Operar el robot. • Ser compañero del robot (compartir tareas). • Ser mecánico o programador del robot. • Ser espectador. Verlo, pero no interactuar nada. • No querría trabajar con robots.
3.3	¿Con qué genero se identifica más?	• Hombre • Mujer • Ninguna de las opciones anteriores • Prefiero no responder
3.4	Año de nacimiento	• Campo numérico (4 dígitos)
3.5	Años aproximados trabajando	• Campo numérico (2 dígitos sin decimales)

Annex 8 Contact email to participants (English)

Dear XXXXX,

My name is Juan Montero, associate professor in the Department of Business Management at the Universitat Rovira i Virgili. I am currently doing my Doctoral dissertation whose object of study is to analyze factors for the acceptance of robots by employees, and their impact on the corporate reputation of organizations.

The present study has an international focus and has been based on the different applicable theories on technological acceptance and corporate reputation management.

Through this email, I request your collaboration by answering the questionnaire through the link https://survey.zohopublic.eu/zs/A9BjI0

The anonymity and confidentiality of all responses is guaranteed. In addition, the data obtained will be treated in aggregate form, exclusively by the research team, guaranteeing its use for exclusively research purposes.

As a result of the study, all participants are offered the possibility of receiving an executive report with the main results obtained. To receive it, please send an email to juanandres.montero@urv.cat and I would be more than pleased sending it to you.

Thank you very much in advance.

Juan Montero Vilela
Associate Professor URV
Department of Business Management

Annex 9 Contact email to participants (Spanish)

Estimad@ XXXXX,

Mi nombre es Juan Montero, profesor asociado en el departamento de Gestión de Empresas de la Universitat Rovira i Virgili. Actualmente estoy realizando mi Tesis Doctoral cuyo objeto de estudio consiste en analizar factores para la aceptación de los robots por parte de los empleados, y su impacto en la reputación corporativa de las organizaciones.

El presente estudio tiene un enfoque internacional y se ha basado en las diferentes teorías aplicables sobre la aceptación tecnológica y gestión de la reputación corporativa.

A través de este mail, solicito su colaboración respondiendo al cuestionario a través del enlace https://survey.zohopublic.eu/zs/mIBjEM

Se garantiza el anonimato y confidencialidad de todas las respuestas. Además, los datos obtenidos serán tratados de forma agregada, exclusivamente por el equipo de investigación garantizándose su uso con fines exclusivamente investigadores.

Como resultado del estudio, a todos los participantes se les ofrece la posibilidad de recibir un informe ejecutivo con los principales resultados obtenidos. Para recibirlo, tan solo tiene que enviar un email al juanandres.montero@urv.cat solicitando el mismo, y estaré encantado de hacérselo llegar.

Muchas gracias de antemano.

Juan Montero Vilela
Profesor asociado URV
Departamento de Gestión de Empresas

Annex 10 Questionnaire in Japanese

UNIVERSITAT ROVIRA i VIRGILI

職場におけるロボット の導入と 企業の評判に関する調査

このアンケート 調査について

このアンケート 調査研究は職場におけるロボット の導入に関するものです。
　現在，ロボット はいろいろな形で職場に導入さ れており，特定の作業を行う 際にそれを完全に自動化し たり，部分的に自動化し たり するのに使われています。たとえば，製造現場では多関節ロボット のような産業用ロボット が使われ，オフィスではコンピュータプログラムがさまざまな事務作業を代行し ています。そこではロボット が人間と協力して仕事をこなし たり，あるいは人間に代わって仕事をしています。この調査では，あらゆるタイプのロボット を調査対象としています。
　あなたが現在，仕事をしている場合は，現在のご自分の職位や役割に基づいてこのアンケート 調査にお答えく ださい。あなたが学生である場合は，将来的にやり たい仕事を念頭に答えてく ださい。またあなたがすでに退職さ れている場合は，最後に行っていた仕事の経験に基づいて回答をお願いいたします。
　このアンケート 調査への回答には，およそ5分間を要します。
　アンケート 調査への回答にあたっては，個人が特定されることはなく，すべての回答データは匿名性を保った形で，外部に一切漏れることがないよう 厳密に保管します。回答の分析は，このアンケート 調査を実施している研究チームのメンバーのみによって行われます。このアンケート 調査ならびに本研究についてご質問・ご意見がある場合は，juanandres.montero@urv.catにメールしてく ださい。
　また，本アンケート 調査研究の結果について興味がある場合は，それに関する概要を後日送付しますので，juanandres.montero@urv.catにメールしてく ださい。
　アンケート 調査へのご協力の程，何卒よろしく お願い申し上げます。

ロボット 技術の導入

あなたの働いている会社が，あなたが直接的に関わりを持つ仕事に対してロボット を導入しようとしていると想定してく ださい。以下のそれぞれの文について，あなたの意見を「 0：全く そう は思わない」から「 10：全く その通り だと 思う 」までの11段階から1つだけ選んでく ださい。

*私の職場がロボット化されるのであれば，私はそれに対応していく意志がある。

全く そうは思わない										全く その通り だと思う
0	1	2	3	4	5	6	7	8	9	10

*私の職場がロボット化されるのであれば，私はそれに対応していくことだろう。

全く そうは思わない										全く その通り だと思う
0	1	2	3	4	5	6	7	8	9	10

*職場にロボットを導入することは良い考えである。

全くそうは思わない										全くその通りだと思う
0	1	2	3	4	5	6	7	8	9	10

*職場にロボットを導入することは賢い選択である。

全くそうは思わない										全くその通りだと思う
0	1	2	3	4	5	6	7	8	9	10

*職場へのロボットの導入は進歩である。

全くそうは思わない										全くその通りだと思う
0	1	2	3	4	5	6	7	8	9	10

*職場にロボットを導入することは効果的なアイデアである。

全くそうは思わない										全くその通りだと思う
0	1	2	3	4	5	6	7	8	9	10

*日々ロボットと共に働くことは有益である。

全くそうは思わない										全くその通りだと思う
0	1	2	3	4	5	6	7	8	9	10

*ロボットと共に働くことで，私にとって重要な目標を達成するチャンスが増えていく。

全くそうは思わない										全くその通りだと思う
0	1	2	3	4	5	6	7	8	9	10

*ロボットと共に働くことで，私は仕事をより早く行うことができる。

全くそうは思わない										全くその通りだと思う
0	1	2	3	4	5	6	7	8	9	10

*ロボットと共に働くことで，私の生産性が向上する。

全くそうは思わない										全くその通りだと思う
0	1	2	3	4	5	6	7	8	9	10

*ロボットとどのように共に働けば良いかを学習することは，私にとって簡単である。

全くそうは思わない										全くその通りだと思う
0	1	2	3	4	5	6	7	8	9	10

*私にとってロボットとのやり取り（操作等）は，明確で理解しやすいものである。

全くそうは思わない										全くその通りだと思う
0	1	2	3	4	5	6	7	8	9	10

*ロボットと共に働くことは簡単である。

全くそうは思わない										全くその通りだと思う
0	1	2	3	4	5	6	7	8	9	10

*ロボットと共に働くことに熟練していくことは，私にとって簡単である。

全くそうは思わない										全くその通りだと思う
0	1	2	3	4	5	6	7	8	9	10

*私にとって大切な人々は，私がロボットと共に働くべきだと思うだろう。

全くそうは思わない										全くその通りだと思う
0	1	2	3	4	5	6	7	8	9	10

*私の行動に影響を及ぼす人々は，私がロボットと共に働くべきだと思うだろう。

全くそうは思わない										全くその通りだと思う
0	1	2	3	4	5	6	7	8	9	10

*私がその意見を尊重する人々は，私がロボットと共に働くことを好むだろう。

全くそうは思わない										全くその通りだと思う
0	1	2	3	4	5	6	7	8	9	10

*ロボットと共に働くことにはリスクが伴う。

全くそうは思わない										全くその通りだと思う
0	1	2	3	4	5	6	7	8	9	10

*ロボットと共に働くことには，非常に大きな不確実性が付きまとう。

全くそうは思わない										全くその通りだと思う
0	1	2	3	4	5	6	7	8	9	10

*ロボットと共に働く仕事は，そうではない仕事に比べて，よりリスクが伴う。

全くそうは思わない										全くその通りだと思う
0	1	2	3	4	5	6	7	8	9	10

*私はロボットと共に働くために必要な資質を持っている。

全くそうは思わない										全くその通りだと思う
0	1	2	3	4	5	6	7	8	9	10

*私はロボットと共に働くために必要な知識を持っている。

全くそうは思わない										全くその通りだと思う
0	1	2	3	4	5	6	7	8	9	10

*ロボットは，現在私が使っているシステムや技術と適合・両立する。

全くそうは思わない										全くその通りだと思う
0	1	2	3	4	5	6	7	8	9	10

*ロボットの利用に当たって必要な時には，他の人からの支援や助力を受けることができる。

全くそうは思わない										全くその通りだと思う
0	1	2	3	4	5	6	7	8	9	10

ロボット技術の導入 — 因子

あなたは，ロボットと共に働くことについてどのような感情を持つでしょうか。以下の用語で表される感情それぞれについて，あなたが実際にどのように感じるかを「0：全くそのようには感じない」から「10：全くその通り感じる」までの11段階から1つだけ選んでください。

*興味深いと思う

全くそのようには感じない										全くその通り感じる
0	1	2	3	4	5	6	7	8	9	10

*ワクワクする

全くそのようには感じない										全くその通り感じる
0	1	2	3	4	5	6	7	8	9	10

*断固としてロボットと共に働きたいと思う

全くそのようには感じない										全くその通り感じる
0	1	2	3	4	5	6	7	8	9	10

*熱烈にロボットと共に働くことを支持する

全くそのようには感じない										全くその通り感じる
0	1	2	3	4	5	6	7	8	9	10

*誇りに思う

全くそのようには感じない										全くその通り感じる
0	1	2	3	4	5	6	7	8	9	10

*刺激（触発）される

全くそのようには感じない										全くその通り感じる
0	1	2	3	4	5	6	7	8	9	10

*能力が強化されると思う

全くそのようには感じない										全くその通り感じる
0	1	2	3	4	5	6	7	8	9	10

*より積極的・活発になると感じる

全くそのようには感じない										全くその通り感じる
0	1	2	3	4	5	6	7	8	9	10

*悩ましいと感じる

全くそのようには感じない										全くその通り感じる
0	1	2	3	4	5	6	7	8	9	10

*動揺する

全くそのようには感じない										全くその通り感じる
0	1	2	3	4	5	6	7	8	9	10

*混乱する

全くそのようには感じない										全くその通り感じる
0	1	2	3	4	5	6	7	8	9	10

*恥ずかしいと思う

全くそのようには感じない										全くその通り感じる
0	1	2	3	4	5	6	7	8	9	10

*おびえる

全くそのようには感じない										全くその通り感じる
0	1	2	3	4	5	6	7	8	9	10

*敵意を持つ

全くそのようには感じない										全くその通り感じる
0	1	2	3	4	5	6	7	8	9	10

*恐れる

全くそのようには感じない										全くその通り感じる
0	1	2	3	4	5	6	7	8	9	10

*イライラする

全くそのようには感じない										全くその通り感じる
0	1	2	3	4	5	6	7	8	9	10

*警戒する

全くそのようには感じない										全くその通り感じる
0	1	2	3	4	5	6	7	8	9	10

*不安になる

全くそのようには感じない										全くその通り感じる
0	1	2	3	4	5	6	7	8	9	10

*用心深くなる

全くそのようには感じない										全くその通り感じる
0	1	2	3	4	5	6	7	8	9	10

*いら立つ

全くそのようには感じない										全くその通り感じる
0	1	2	3	4	5	6	7	8	9	10

ロボット技術の導入 — 独立変数

最後の質問ページになります。あなたご自身についての質問もありますが，すべて匿名のまま処理されます。

*すでにロボットと共に働いていますか？

- ◯ はい
- ◯ いいえ

*すでにロボットと共に働いている場合，あなたの仕事におけるロボットとの関係は，主としてどのようなものですか？

- ◯ ロボットと共に働いたことがない。
- ◯ ロボットを管理・監督する役割を担っている。
- ◯ ロボットをオペレータとして操作している。
- ◯ ロボットと共に働いており，いわば同僚としての関係にある。
- ◯ ロボットの整備担当者やプログラマとしての役割を担っている。
- ◯ 直接的な関わりはなく，傍観者である。

*これからロボットと共に働く場合，どのような役割を果たしたいですか？

- ◯ ロボットを管理・監督する役割。
- ◯ ロボットのオペレータ。
- ◯ ロボット共に働く，いわば同僚としての立場。
- ◯ ロボットの整備担当者やプログラマ。
- ◯ 直接的な関わりのない傍観者。
- ◯ ロボットと共に働きたくない。

*あなたの性別をお答えください。

- ◯ 男性
- ◯ 女性
- ◯ その他
- ◯ 答えたくない

*あなたの年齢をお答えください。

[ ]

*あなたの実務経験年数をお答えください（年単位）。

[ ]

Annex 11 Questionnaire in German

UNIVERSITAT ROVIRA i VIRGILI

WIE DIE AKZEPTANZ VON ROBOTERN AM ARBEITSPLATZ DEN REPUTATION DES UNTERNEHMENS BEEINFLUSST

Einführung in den Fragebogen

Diese Forschung analysiert die Akzeptanz von Robotern bei der Arbeit.

Roboter nehmen sehr unterschiedliche Formen an und können Aufgaben ohne menschliches Eingreifen ganz oder teilweise unterstützen oder ausführen. Beispielsweise ist es in der Industrie normalerweise ein Knickarmroboter, während der Roboter im Verwaltungsbereich ein Computerprogramm sein kann, das sowohl soziale als auch Managementaufgaben erfüllt und Menschen ersetzt und/oder hilft.

In dieser Studie beziehen wir uns auf alle Arten von Robotern. Wenn Sie derzeit berufstätig sind, beantworten Sie die Fragen unter Berücksichtigung Ihrer aktuellen Position. Wenn Sie Student, Rentner oder Arbeitsloser sind, beantworten Sie die Fragen in Bezug auf Ihre letzte Stelle oder diejenige, auf die Sie sich vorbereiten. Die Beantwortung dieses Fragebogens dauert ca. 5 Minuten.

Die Antworten sind streng vertraulich und anonym. Die Antworten werden ausschließlich vom Forschungsteam ausgewertet. Um Fragen zu beantworten oder Informationen in Bezug auf die Studie oder die in diesem Dokument enthaltenen Informationen zu erweitern, können Sie eine E-Mail an juanandres.montero@urv.cat senden.

Wenn Sie daran interessiert sind, eine Zusammenfassung mit den Schlussfolgerungen dieser Studie zu erhalten, Sie können es anfordern, indem Sie an dieselbe E-Mail Adresse juanandres.montero@urv.cat schreiben.

Danke für Ihre Kooperation.

Technologische Akzeptanz von Robotern

Denken Sie daran, dass Ihr Unternehmen Roboter einsetzt, welche eine direkte Beziehung zu Ihrer Arbeit haben, geben Sie Ihre Meinung mit den folgenden Aussagen an, von 0 stimme überhaupt nicht zu bis 10 stimme voll und ganz zu:

* Angenommen, ich hätte Zugang zu einem robotisierten Arbeitsplatz, dann würde ich beabsichtigen, daran zu arbeiten.

stimme überhaupt nicht zu										stimme voll und ganz zu
0	1	2	3	4	5	6	7	8	9	10

*Angenommen, ich hätte Zugang zu einem robotisierten Arbeitsplatz, dann würde ich voraussetzen, daran zu arbeiten.

stimme überhaupt nicht zu										stimme voll und ganz zu
0	1	2	3	4	5	6	7	8	9	10

*Der Einsatz von Robotern am Arbeitsplatz wäre eine gute Idee.

stimme überhaupt nicht zu										stimme voll und ganz zu
0	1	2	3	4	5	6	7	8	9	10

*Der Einsatz von Robotern am Arbeitsplatz wäre ein kluger Schachzug.

stimme überhaupt nicht zu										stimme voll und ganz zu
0	1	2	3	4	5	6	7	8	9	10

*Der Einsatz von Robotern am Arbeitsplatz wäre ein Schritt nach vorn.

stimme überhaupt nicht zu										stimme voll und ganz zu
0	1	2	3	4	5	6	7	8	9	10

*Der Einsatz von Robotern am Arbeitsplatz wäre eine effective Idee.

stimme überhaupt nicht zu										stimme voll und ganz zu
0	1	2	3	4	5	6	7	8	9	10

*Ich würde es für sinnvoll halten, täglich mit Robotern zu arbeiten.

stimme überhaupt nicht zu … stimme voll und ganz zu

0 1 2 3 4 5 6 7 8 9 10

*Die Arbeit mit Robotern würde meine Chancen erhöhen, wichtige Ziele zu erreichen.

stimme überhaupt nicht zu … stimme voll und ganz zu

0 1 2 3 4 5 6 7 8 9 10

*Die Arbeit mit Robotern würde es mir ermöglichen, Aufgaben schneller zu erledigen.

stimme überhaupt nicht zu … stimme voll und ganz zu

0 1 2 3 4 5 6 7 8 9 10

*Die Arbeit mit Robotern würde meine Produktivität steigern.

stimme überhaupt nicht zu … stimme voll und ganz zu

0 1 2 3 4 5 6 7 8 9 10

*Die Arbeit mit Robotern zu erlernen, wäre für mich einfach.

stimme überhaupt nicht zu … stimme voll und ganz zu

0 1 2 3 4 5 6 7 8 9 10

*Meine Interaktion mit dem Roboter würde klar und verständlich sein.

stimme überhaupt nicht zu — stimme voll und ganz zu

0 1 2 3 4 5 6 7 8 9 10

*Die Arbeit mit Robotern wäre einfach.

stimme überhaupt nicht zu — stimme voll und ganz zu

0 1 2 3 4 5 6 7 8 9 10

*Es wäre für mich einfach, mir die Kentnisse beim Arbeiten mit Robotern anzueignen.

stimme überhaupt nicht zu — stimme voll und ganz zu

0 1 2 3 4 5 6 7 8 9 10

*Menschen, die mir wichtig sind, denken, dass ich mit Robotern arbeiten sollte.

stimme überhaupt nicht zu — stimme voll und ganz zu

0 1 2 3 4 5 6 7 8 9 10

*Menschen, die mein Verhalten beeinflussen, meinen, ich sollte mit Robotern arbeiten.

stimme überhaupt nicht zu — stimme voll und ganz zu

0 1 2 3 4 5 6 7 8 9 10

*Menschen, deren Meinung ich schätze, würden es vorziehen, wenn ich mit Robotern arbeiten würde.

stimme überhaupt nicht zu										stimme voll und ganz zu
0	1	2	3	4	5	6	7	8	9	10

*Die Arbeit mit Robotern ist riskant.

stimme überhaupt nicht zu										stimme voll und ganz zu
0	1	2	3	4	5	6	7	8	9	10

*Die Arbeit mit Robotern wäre mit zu viel Unsicherheit verbunden.

stimme überhaupt nicht zu										stimme voll und ganz zu
0	1	2	3	4	5	6	7	8	9	10

*Im Vergleich zu anderen Arbeitsplätzen sind die Arbeitsplätze mit Robotern risikoreicher.

stimme überhaupt nicht zu										stimme voll und ganz zu
0	1	2	3	4	5	6	7	8	9	10

*Ich würde über die erforderlichen Ressourcen verfügen, um mit Robotern zu arbeiten.

stimme überhaupt nicht zu										stimme voll und ganz zu
0	1	2	3	4	5	6	7	8	9	10

*Ich hätte die erforderlichen Kenntnisse für die Arbeit mit Robotern.

stimme überhaupt nicht zu										stimme voll und ganz zu
0	1	2	3	4	5	6	7	8	9	10

*Die Roboter wären mit den derzeitigen Systemen und Technologien, die ich verwende, kompatibel.

stimme überhaupt nicht zu										stimme voll und ganz zu
0	1	2	3	4	5	6	7	8	9	10

*Im Bedarfsfall hätte ich Unterstützung oder Hilfe von anderen.

stimme überhaupt nicht zu										stimme voll und ganz zu
0	1	2	3	4	5	6	7	8	9	10

Akzeptanz der Robotertechnologie - Faktoren -

Denken Sie darüber nach, wie Sie sich bei der Arbeit mit einem Roboter fühlen, und bewerten Sie die folgenden Adjektive von 0, wenn Sie gar nichts fühlen, bis 10, wenn Sie es intensiv fühlen:

*INTERESSIERT

fühlen Sie gar nicht										fühlen Sie intensiv
0	1	2	3	4	5	6	7	8	9	10

*AUFGEREGT

fühlen Sie gar nicht										fühlen Sie intensiv
0	1	2	3	4	5	6	7	8	9	10

*BESTIMMT/ENTSCHLOSSEN

fühlen Sie gar nicht										fühlen Sie intensiv
0	1	2	3	4	5	6	7	8	9	10

*ENTUSIASTISCH

fühlen Sie gar nicht										fühlen Sie intensiv
0	1	2	3	4	5	6	7	8	9	10

*STOLZ

fühlen Sie gar nicht										fühlen Sie intensiv
0	1	2	3	4	5	6	7	8	9	10

*INSPIRIERT

fühlen Sie gar nicht										fühlen Sie intensiv
0	1	2	3	4	5	6	7	8	9	10

*STARK

fühlen Sie gar nicht										fühlen Sie intensiv
0	1	2	3	4	5	6	7	8	9	10

*AKTIV

fühlen Sie gar nicht										fühlen Sie intensiv
0	1	2	3	4	5	6	7	8	9	10

*NOT LEIDEND

fühlen Sie gar nicht										fühlen Sie intensiv
0	1	2	3	4	5	6	7	8	9	10

*VERÄRGERT

fühlen Sie gar nicht										fühlen Sie intensiv
0	1	2	3	4	5	6	7	8	9	10

*VERWIRRT

fühlen Sie gar nicht										fühlen Sie intensiv
0	1	2	3	4	5	6	7	8	9	10

*BESCHÄMT

fühlen Sie gar nicht										fühlen Sie intensiv
0	1	2	3	4	5	6	7	8	9	10

*VERÄNGSTIGT

fühlen Sie gar nicht										fühlen Sie intensiv
0	1	2	3	4	5	6	7	8	9	10

*FEINDLICH

fühlen Sie gar nicht										fühlen Sie intensiv
0	1	2	3	4	5	6	7	8	9	10

*BESORGT

fühlen Sie gar nicht										fühlen Sie intensiv
0	1	2	3	4	5	6	7	8	9	10

*REIZBAR

fühlen Sie gar nicht										fühlen Sie intensiv
0	1	2	3	4	5	6	7	8	9	10

*ALAMIERT

fühlen Sie gar nicht										fühlen Sie intensiv
0	1	2	3	4	5	6	7	8	9	10

*NERVÖS

fühlen Sie gar nicht										fühlen Sie intensiv
0	1	2	3	4	5	6	7	8	9	10

*AUFMERKSAM

fühlen Sie gar nicht										fühlen Sie intensiv
0	1	2	3	4	5	6	7	8	9	10

*VERUNSICHERT

fühlen Sie gar nicht										fühlen Sie intensiv
0	1	2	3	4	5	6	7	8	9	10

Akzeptanz der Robotertechnologie - unabhängige Variablen -

Die folgenden Fragen, wie auch der gesamte Fragebogen, werden anonym behandelt.

*Haben Sie bereits mit Robotern gearbeitet?

- ◯ Ja
- ◯ Nein

*Wenn Sie bereits mit Robotern gearbeitet haben, war Ihre Interaktion mit Robotern bei der Arbeit hauptsächlich...

- ◯ Ich habe nicht mit Robotern gearbeitet.
- ◯ Aufsichtsfunktion.
- ◯ Interaktion mit dem Benutzer.
- ◯ Vorzeigerolle
- ◯ Rolle des Mechanikers oder Programmierers.
- ◯ Rolle als Zuschauer.

*Wenn Sie in Zukunft mit Robotern arbeiten würden, hätten Sie gerne die...

- ◯ Aufsichtsfunktion.
- ◯ Interaktion mit dem Benutzer.
- ◯ Vorzeigerolle
- ◯ Rolle des Mechanikers oder Programmierers.
- ◯ Rolle als Zuschauer.
- ◯ Ich würde lieber nicht mit Robotern arbeiten

*Ihr Geschlecht

- ◯ Mann
- ◯ Frau
- ◯ Keines der oben genannten
- ◯ Ich möchte diese Frage nicht beantworten.

*Alter

[ ]

*Berufserfahrung in Jahren (ungefähr)

[ ]

Annex 12 Certificate Data Protection compliance

UNIVERSITAT ROVIRA i VIRGILI

CEIPSA
Comitè Ètic d'Investigació en Persones, Societat i Medi Ambient

ENGLISH

AITOR GÓMEZ GONZÁLEZ, PRESIDENT OF THE ETHICAL COMMITTEE CONCERNING RESEARCH INTO PEOPLE, SOCIETY AND THE ENVIRONMENT OF THE UNIVERSITAT ROVIRA I VIRGILI (CEIPSA),

I CERTIFY:

That the thesis by Mr. Juan Andrés Montero Vilela (Thesis director: Dr. Jorge De Andrés Sànchez), entitled:

"HOW ROBOT ACCEPTANCE AT WORK INFLUENCE CORPORATE REPUTATION"

Code: CEIPSA-2023-TD-0047

Was carried out, in accordance with the documentation presented, following the principles and evaluation criteria of this Committee:

- The project proposal presented was in accordance with good scientific practices and the values of scientific correctness, training, justice, solidarity, protection of vulnerable subjects, dignified treatment, personal autonomy, privacy, confidentiality, reparation of damage and respect for human rights.
- The project proposal complied, in general, with the currently applicable general European, Spanish, and Catalan legislation, and with the URV's own regulations on R+D+I.
- The project proposal complied, in general, with the methodological, ethical, and legal requirements within the scope of CEIPSA's competences and in relation to its:

  a) Social value as a project.
  b) Research staff.
  c) Methodology.
  d) Specific ethical aspects, namely the risks and benefits, the measures regarding damage prevention and repair, the processes regarding selection and recruitment, the protection of vulnerable subjects, and the aspects relating to information, consent, privacy and confidentiality.
  e) Compliance with the documentation, namely the informed consent document, the document confirming file security, the authorizations, and the current regulatory requirements.
- During the review of the documentation, an incident was detected regarding the participants right to information, which meant that there was a partial case of non-compliance with the provisions of articles 13 and 14 of European General Data Protection Regulation.

Signed by

AITOR GÓMEZ GONZÁLEZ - DNI 38140434v
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Dr Aitor Gómez González
CEIPSA URV President

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