UNIVERSITAT ROVIRA I VIRGILI

ROBOTS, CYBORGS AND HUMANS: A FUTURISTIC MODEL OF CONSUMER BEHAVIOR IN SERVICES. AN INTERNATIONAL STUDY IN MEDICAL SERVICES SECTOR

Ala' Ali Mohammad Almahameed

UNIVERSITAT
ROVIRA i VIRGILI

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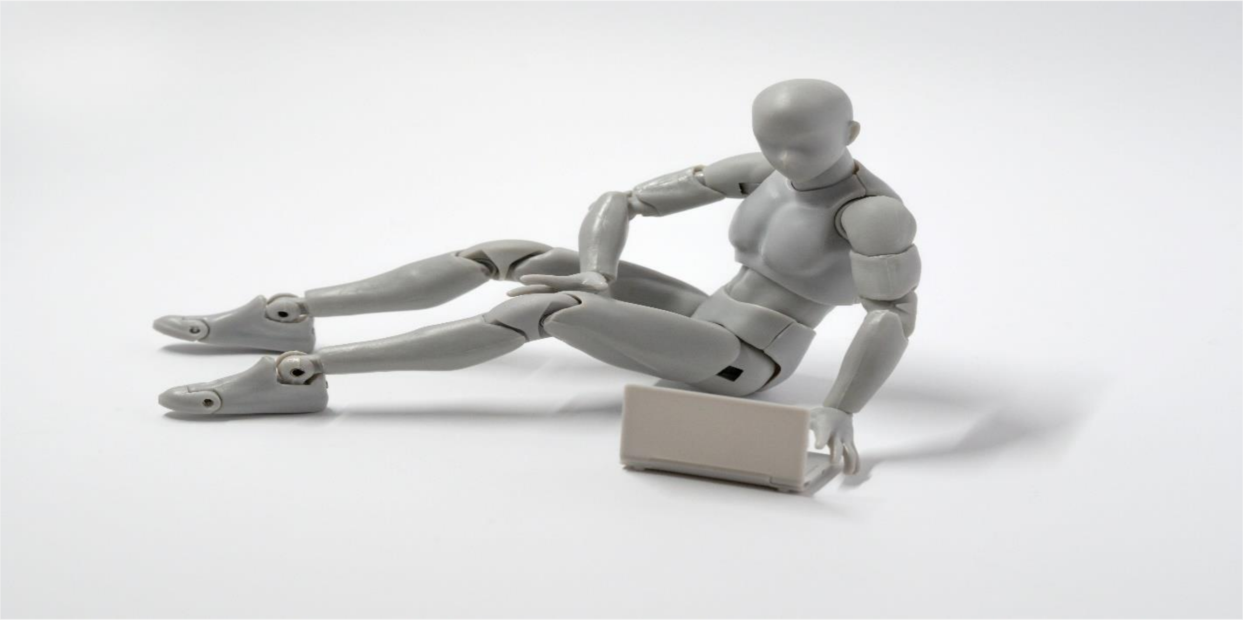
ALA' ALI ALMAHAMEED



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ALA' ALI ALMAHAMEED

Robots, Cyborgs, and Humans. A Model of Consumer Behavior in Services: A Study in the Healthcare Services Sector

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Supervised by

Dr. Mario Arias-Oliva

Dr. Jorge Pelegrín-Borondo

Humanistic Studies

Department of Business

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UNIVERSITAT
ROVIRA i VIRGILI

Department of Business Management

Campus Catalunya
Avinguda Catalunya, 35
43002 - Tarragona
Spain

WE STATE that the present study, entitled *Robots, Cyborgs, and Humans. A Model of Consumer Behavior in Services: A Study in the Healthcare Services Sector*, presented by ALA' ALI ALMAHAMEED for the award of the degree of Doctor, has been carried out under our supervision at the Department of Business of this university, and that it fulfils all the requirements to receive the International Doctorate Distinction.

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Doctoral Thesis Supervisors

ARIAS OLIVA MARIO - 02878808J
Firmado digitalmente por ARIAS OLIVA MARIO - 02878808J
Fecha: 2020.06.09 09:27:56 +02'00'

Dr. Mario Arias-Oliva

PELEGRIN BORONDO JORGE - 16563058E
Firmado digitalmente por PELEGRIN BORONDO JORGE - 16563058E
Fecha: 2020.06.09 10:40:49 +02'00'

Dr. Jorge Pelegrín-Borondo

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Abstract

This research developed a model that can be used to identify the choice criteria among robot, cyborg, and human services, analyzing in the healthcare service sector. The research proposes a futuristic use of robot and cyborg as surgeons in an eye surgery. Thereafter, the developed model has been applied to investigate the intention to use each surgeon (i.e. robot surgeon, cyborg surgeon, and human surgeon). The data was collected from the students of Jordanian universities and analyzed using the PLS-SEM technique. According to the research results, effort expectancy, performance expectancy, perceived risk, and social influence showed a significant impact on intention to use robot services. However, the results of the cyborg service model confirmed the significant impact of effort expectancy, arousal, performance expectancy, and social influence on the intention to use cyborg services. Furthermore, effort expectancy and social influence confirmed their significant impact on the intention to use human services. Also, the results of the three models showed that the variables social influence and effort expectancy significantly affected the intention to use these surgical services, with a different intensity between the models for effort expectancy. In this context, the impact of social influence gives a general idea about the nature of the healthcare sector in Jordan, where a part of society gives more attention to the recommendation from others (e.g. family members and friends, users) while choosing their surgeons. Also, the effort expectancy impact contributes to patients' expectations of simplicity, in terms of use and interaction with the proposed surgeons. The multigroup analysis confirmed that the models' variables are affecting the intention to use cyborg and human service, and cyborg and robots in the same way. However, the differences were confirmed between robot and human cyborgs in terms of the impact of effort expectancy on the intention to use these services. On the other side, the ANOVA t-test confirmed the differences of participants' intention to choose among the proposed surgeons, which was confirmed by their preference of the human surgeon over the cyborg and robot surgeons, respectively. As a result, the acceptance of the robot and cyborg technologies by a part of the society could give an idea about the expected struggle in the future among developing robots and enhancing human capabilities. Besides, this research opens a new line of researches related to the acceptance of cyborg technology as an entity and robot as an autonomous device that could be used in critical service settings (i.e. surgeries).

Keywords: Cyborg, Robot, Human Services, Technology Acceptance.

UNESCO Codes: 5306.02 Technological innovation.

Chapter1: Introduction

1.1 Introduction

Modern-day innovative technologies are progressively replacing humans to carry out complicated tasks in various sectors, such as in healthcare, education, transportation, and manufacturing (Waytz, Heafner, & Epley, 2014). Consequently, since robots use sophisticated technologies in order to deliver refined and better results, there is an underlying need for enhancing value additions by humans to the economy (Aaron & Anderson, 2014). Likewise, several subject matter experts have expressed their worries about jobs that humans may lose to robots, which in turn can increase the unemployment rate. However, these worries haven't considered the possibilities of enhancing mankind's natural capabilities to be able to compete with a robot's sophisticated capabilities (Palese, 2012). In this context, the emergence of the technological implants for therapy and/or improvement of the human capabilities opens a new era in human-machine interaction. The term cyborg (Cybernetic Organism) is introducing the human with new capabilities or in short a "Superhuman ", by using temporary devices (i.e. wearables) or by implanting electronic devices into humans' body (Park, 2014). Despite the fact that human-machine integration is still under the development process, cyborg might not be considered as a new term, because it has been emerged in 1960 by Clynes and Kline (1960) and they claimed that modifying the human body system to match the requirements of the outer space environment could be more reasonable than offering to humans an earth environment in the outer space. They believed in the possibility of creating artifact-organism systems. Accordingly, scientists started to develop a combination between humans and machines in which it can enhance or compensate human capabilities. For healthcare purposes, as the number of individuals who are acquiring such devices is growing, the available number of devices that could be implanted into the human body are also progressively rising (Fang, Lee, Permana, Ghorbani, & Cosic, 2011; Mackert & Harrison, 2009; Reinares-Lara, Olarte-Pascual, Pelegrin-borondo, & Pino, 2016). Most of the developed implantable devices across the past decade have been utilized for the healthcare applications, such as paralyzed limbs control, pacemakers, cochlear and vision improvement devices (Raatikainen et al., 2015), and some implantable devices are being used to enhance human capabilities, such as memory, vision, hearing, physical strength, and moral enhancement (Buchanan-Oliver & Cruz, 2011; Gasson, Kosta, & Bowman, 2012; Jotterand, 2014; Reinares-Lara et al., 2016). For instance, radio frequency identification (RFID) chips can be implanted under human skin to be used for access control, personal identification, credit card, and mobile payments by using near-field communication (NFC) technology (Adam & Wilkes, 2016). Furthermore, the cochlear implants represent the first interaction between the human brain and the machines to replace the lost sounds by allowing the brain to recover the sense of hearing. Also, it could be used to enhance the hearing ability of healthy people (Christie & Bloustien, 2010). Another example is the brain-computer interfaces (BCI), which have been used for the restoration of motor control for paralyzed patients and enables communication with them by decoding their thoughts (Chaudhary, Birbaumer, & Ramos-Murguialday, 2016). The decoding of brain signals is done through the skull's surface by using Electroencephalography (EEG) or by implanted electrodes and then translating these signals into motion commands to a cursor or a robotic arm (Shih, Krusienski, & Wolpaw, 2012). An additional example of brain-machine interaction is the stimulation of the brain by using electrical signals sent for performing specific commands, such as controlling the prosthetic hand and feeling the touch stimuli on the human body (Domingo, 2012). Furthermore, many researchers and scientists believe that technological implants will enable humans to log onto the Internet, access different databases, be able to speak new languages fluently, and to help people with failing memories. It promises in making humans fundamentally different by radically changing their capabilities. In addition, humans will be able to remotely control devices through thoughts (McGee & Maguire, 2007). Meanwhile, the wearables are defined as electronic devices that could be worn or removed upon the need of humans to increase their abilities. Technological tattoos, fitness trackers, smartwatches, and smart glasses are representing some examples of wearables technology (Firger, 2015). The attention toward these technologies is trending among technology leaders and research centers. For example, the brain implants to enhance human memory have been considered as the most innovative technology advancement by the MIT research review (Cohen, 2013). In the same context, the advancement of nanotechnology has been supporting the development of the implanted devices to become smaller with the possibilities of implanting it into the human bodies. The term Nanoimplants represents the implanted devices that could be inserted inside the humans' body to increase their capabilities.

Since the last half-century, the integration between robots and humans has increased vastly. What had been considered science fiction has become a reality, especially in applications where the robot has replaced or is collaborating with humans (Salem, Lakatos, Amirabdollahian, & Dautenhahn, 2015). Alternatively, such advancement in technology must not be categorized as a threat as it can lead to potential opportunities for consumers to get better services and outcomes in relative fields where these technologies will be applied. In this sense, the relationship between robots and humans differ in nature from the relationship between humans and other machines. The robot could be a simple machine or a complex autonomous mobile robot. They can be involved in a humans' daily life and have a mutual social interaction (Rogers, 2004). In this context, the Human-Robot Interaction (HRI) is a scope of research concerned in evaluating, designing, and understanding the use of robotic systems in the human own environment. The communication between robots and humans is required to establish the interaction process, and this communication can be conducted remotely (i.e. humans and robots are not physically in the same place) or proximate (i.e. both are physically in the same place). With these types of communication, different interaction-based classifications are used for robots. These classifications are relating to social interaction, physical manipulation, and mobility. For example, proximate interaction with mobility will form robot-assistant systems. Additionally, empathy, sociability, and cognitive characteristics are associated with robots' social interaction ability. On the other hand, remote interaction with mobile robots is representing supervisory and teleoperation control applications (Goodrich, 2008). Likewise, the applications of mobile robots have grown significantly for the use of outdoor and indoor applications in different sectors, especially for risky applications and in places or operations where human access is difficult or impossible (Sharifi, Young, Chen, Clucas, & Pretty, 2016). Also, they are used in factories, military applications, healthcare, research and rescue, security, and homes (Shneier & Bostelman, 2015). Moreover, Sheridan (2016) classified the robots based on their applications into:

1. **Supervisory control robots**: these types of robots can perform a series of automated tasks based on a computer program with the ability to send feedback to the operator. It can be found in warehouses, hospitals, and offices to deliver different types of materials.
2. **Robots control for hazardous environments**: these robots are used in accessing undersea, outer space, terrestrial, and airborne missions. They are called as a teleoperator robot if physical manipulation is associated with mobility and human control. Whilst, automated control via computer programs is used in telerobots.
3. **Automated vehicle robots**, as in commercial aircraft, trains, and rail vehicles, where the human is only a passenger.

4. **Social robots**, where social interactions among humans and robots exist, and they are utilized in entertainment, education, and for elderly and children care.

In the healthcare sector, the primary objective of using robots is for improving patient safety and for performing surgical care remotely when needed (Haidegger, Sandor, & Benyo, 2011). This is consistent with the definition of the robot, which is a programmable mechatronic device to perform automatic procedures or the procedures that can be controlled through a computer-based mechanical interface (Diana & Marescaux, 2015). However, making the entire surgical procedure or part of it is imagined as a potential futuristic application of robots (Pessaux et al., 2015). Consequently, the main feature of robotic systems is the ability to gather complex information and to execute physical actions based on this information in a superior way. This ability could enable robots to replace, supplement, or even transcend human performance in different service settings (Taylor, Menciassi, Fichtinger, Fiorini, & Dario, 2016). Also, innovative robots specialized in the healthcare sector have introduced new robots that can be deployed locally or remotely for supporting medical practitioners, such as surgeons. These robots improve the accuracy and the safety of performing surgeries by enhancing and/or imitating complicated human capabilities. However, most of the current robots are supporting surgeons and enhancing their skills and capabilities (Diana & Marescaux, 2015). For instance, the well-known da Vinci robotic surgical system used for different types of surgeries, like heart valve surgeries and prostate cancer therapies. Wherein, the robot is transforming the motions of the surgeon's hand into more accurate and smaller robotic motions (Cooper, Ibrahim, Lyu, & Makary, 2013). Who could compete with that?

It is worth mentioning that the development of the robots isn't limited to hardware devices, but rather it has been extended to include the development of various software that can imitate human abilities over the local and wide area networks. In fact, the development in Artificial Intelligence (AI) and Machine Learning (ML) has contributed clearly in improving the features and abilities of both hardware and software robots (Furmankiewicz, Sołtysik-Piorunkiewicz, & Ziuziański, 2014; Jordan & Mitchell, 2015). For instance, the chatbot is a program that was developed based on AI algorithms to simulate human behavior. For instance, It could be used in language learning and psychotherapy (Shawar & Atwell, 2007). The social bot is also used in social media websites (e.g. Facebook and Twitter) to communicate with users as the human does in different ways and purposes, such as sending automated instant messages for commercial advertisements (Abokhodair, Yoo, & Mcdonald, 2015). Likewise, Babylon health is another application, which was developed in the UK for healthcare purposes. It has the ability to receive patients' calls, evaluate their medical condition, and subsequently determine if the patient requires urgent treatment or if they are to be treated by recommending a specific medicine. The application has been built based on a combination of AI technologies, such as expert systems, ML, and language processing (Heaven, 2018).

Background and Rationale

The development in cyborg technologies requires to investigate consumer behavior toward such technologies. In this sense, the use of nanotechnology in therapy application has been accepted by society and the use of them to improve human capabilities has been partially accepted. Further investigations are ongoing to be able to understand the factors that could stimulate the acceptance of such technologies (Pelegrín-Borondo, Arias-Oliva, Murata, & Souto-Romero, 2018). Eventually, the developments in wearables and insideables to create the cyborg are pointing out to an important concern about how the interaction would be between biological bodies and technological devices, the information processing caused by this interaction, and the impact of this interaction on the environment (Greiner, 2014). Moreover, how will humans perceive cyborg individuals in their society? Are they going to accept their existence? Are they going to interact with them normally? And propose that cyborg will become an employee in any service setting, are people willing to accept the services offered by cyborg? Could they prefer it over human and robot services, for instance? Further information and examples of cyborg technology are mentioned in Chapter 2.

About using robots in healthcare services, Mann, Macdonald, Kuo, Li, and Broadbent (2015) claimed that individuals could be encouraged to follow healthcare behaviors based on robots' advice when compared to the other sources (e.g. humans and computer tablets). Furthermore, they believed that humans could build a stronger relationship with robots than with computer tablets. They considered the appearance as the major factor in formulating human's perception and adherence toward robots. In this regard, there have been numerous studies about consumer acceptance of robots in several areas including serving in restaurants, care of the elderly, and usage in surgeries (Ivanov, Webster, & Berezina, 2017). For instance, Sim and Loo (2015) mentioned in their study about the acceptance of social robots that in order to integrate robots into human daily life, it should be able to assess friendships, understand human expressions, learning from previous experience, and stimulate empathy. Also, Leite (2013) claimed that empathy has a major impact on human-robot interaction. That means, as much as the robot behave empathically, as much as it could be perceived positively, leading to a positive impact on the robot acceptance. In addition to that, other researchers also agreed about the importance of the social abilities of robots to get accepted by the humans (Graaf & Allouch, 2013; Graaf, Allouch, & Klamer, 2015; Heerink, Kröse, Evers, & Wielinga, 2008c). While, superior performance, safety, and acceptable cost should be associated with using robots' surgeons to be accepted as an alternative option to human surgeons (Taylor et al., 2016). More details are explained in Chapter 3.

This research is determined in investigating the acceptance of cyborgs and robots whilst conducting a rational comparison to the humans' capabilities in services, such as healthcare services. However, it is focused on the perspective of the patient which aims to project an idea on how these technology recipients will perceive such innovation and developments and understand their expectations toward these emerging technologies. In fact, healthcare services are intangible and can't be measured, when compared to physical products. Consequently, the interaction between consumers and employees are representing one of the core tools in evaluating service quality (McLaughlin & Kaluzny, 2006; Mosadeghrad, 2013). Furthermore, the employee characteristics should be taken into consideration during the hiring process, as they could be major influencers on consumers' perception of the value that is associated with the offered service (Namasivayam & Denizci, 2006). On the other hand, technology also has another important role in improving service quality and therapy performance in the healthcare sector (Calman, Kitson, & Hauser, 2007). This means, the healthcare institutions must acquire such new technologies and effectively use it through their service processes and among all levels. It has become a necessity and not an option for ensuring business continuity and also to have a competitive advantage for healthcare institutions. In addition to improving the level of the offered services to their patients, it also leads to positively affect patient's health and quality of life (Phichitchaisopa & Naenna, 2013). Further information about human services is explained in Chapter 4.

On the other side, there are relatively a few numbers of researches studied the acceptance of humans to become a cyborg (Montrose, Carroll, Smith, & Oxley, 2017). Olarte-Pascual et al. (2015) studied the acceptance of technological implants to enhance innate capacities. And then they developed the Cognitive-Affective-Normative model (CAN) which explains the acceptance of this technology by evaluating the moderating effect of end-user (Pelegrín-Borondo, Reinares-Lara, Olarte-Pascual, & Garcia-Sierra, 2016). Furthermore, the moderating effect of ethics in the acceptance of neural implants has been investigated by integrating it into the CAN model (Reinares-Lara, Olarte-Pascual, & Pelegrín-Borondo, 2018). Whereas, the unclear area is about the acceptance of these technologies (Cyborg and Robots) in healthcare services without any interference or involvement of the human being. More details about the major theories and models that have been used to study the acceptance of such technologies are explained in Chapter 5.

Normally, researches about the acceptance of technology are conducted for products that are already existing in the market. Whilst, few researchers are interested in the acceptance of technology that is under the development stage (Reinares-Lara et al., 2018), which is the case of this research, because the author believes it will offer valuable basic knowledge for the society about future technologies. Moreover, the comparison somehow will not be easy, because this research is going to compare the choosing criteria between humans, cyborgs, and robots in the healthcare service, which differs as consumer perception could be varied toward them. This may need to combine aspects that can be able to represent the whole parties, such as technological and humanitarian aspects. For instance, the choosing criteria for human service could be based on reputation, technical competence, expertise, and interpersonal skills (Matthews & Feinstein, 1989). And, the technical skills could be the most important criterion when choosing a surgeon (Mavis, Vasilenko, Schnuth, Marshall, & Jeffs, 2005). Meanwhile, the primary care physician could choose the surgeon or the hospital without any input from the patients in some situations. While, the patients' relatives could impact their choice regarding which surgeon or hospital they will perform the surgery (Wilson, Woloshin, & Schwartz, 2007). Furthermore, the surgeon's gender could be not the most important criterion for the patient when choosing a surgeon (Fennema, Meyer, & Owen, 1990). But it may become important in the event that the surgeon will perform some special procedures, such as colonoscopy, or operations involving the genital area, such as gynecological examinations. In those cases, both men and women could prefer patient-physician gender concordance (Fidler, Hartnett, Man, Derbyshire, & Sheil, 2000). What has been mentioned above is in case the services are offered by human-being, what if the services will be performed by either Cyborgs or Robots?

1.2 Impact of Technology on Business and Society

Currently, technology and human life are well integrated and society is more dependent on technology. The use of technology in daily life is rising as its development keeps growing. Humans are using technology in business, education, healthcare, transportation, communications, and so on. While, there are concerns related to the use of technology including safety, privacy, and labor replacement. These concerns require a proper utilization of the technology in which the benefits exceed the side effects (Stahl & Coeckelbergh, 2016). The impact could be seen as a coin, which has two sides; positive and negative. For instance, the use of industrial robots increases the quality and the quantity of production and decreases the time consumed from labor strikes. On the opposite side, the use of such technologies is threatening labor jobs and may subsequently increase the unemployment rate (Qureshi & Syed, 2014).

With regard to the positive impact in healthcare, for instance, technological advancement would be noticed clearly in areas covering first-aid, monitoring of patients, surgeries, and medical treatment (Bajwa, 2014). The combination of AI and robots produced social robots, which have the ability to interact and communicate mutually with patients and elderly people (Torresen, 2018). Also, robot-assistant systems are being used for different types of surgeries. For instance, the surgeon could be staying in Spain and performing surgery in Jordan remotely by using a wide area network (Gerhardus, 2003). Moreover, Neuromotor Prostheses (NMPs) to restore lost motor functions, Deep Brain Stimulation (DBS), pacemakers, implants for health monitoring and cochlear implants are some examples of the impact and innovation of technology in the healthcare sector, which could be reflected positively on the healthcare service quality (Donoghue, Nurmikko, Friehs, & Black, 2004).

In the educational sector, most of the schools, universities, and other educational institutions, especially in the developed countries, have integrated technology and teaching techniques into their institutions to improve education outcomes (Baglari, 2015). Computers, projectors, monitors, mobiles, and tablets are used as aiding tools in education and learning services. The internet is used as an open-source and communication channel, and robots have been recently used in classrooms for different tasks, such as in telepresence, where the teacher is connected to the classroom remotely by a robot (Sharkey, 2016). The navigation systems in vessels, autopilot in aircraft and trains, auto-parking in vehicles, and more, are some examples of the impact of technology in the transportation sector. Moreover, mobile robots can be used to deliver medicine in pharmacies and hospitals, to move materials in warehouses, and so on (Kuyoro, Osisanwo, & Akinsowon, 2015).

Transferring the information is a daily task for both society and institution members. It could be text, audio, and/or video information that can be transferred among all parties and at all levels (Koman & Kundrikova, 2016). TV channels and radio stations are used, for instance, to broadcast important events or political speeches to the audience via satellite, terrestrial, cable, or internet technologies (Keith, 2010). Mobile phones are used to reach anyone and anywhere (Baron, 2009). ML, which is a promising application of AI, is in a continuous development stage. It is used in different applications, such as the recommendations made by online services depending on user preferences and in the smart radio communication terminals, in expectancy of traffic, in smart 5G mobile terminals to control and adjust of transmission power and energy efficiently, and transmission protocol adjustment (Jiang et al., 2016).

It is clear that the impact on each filed is correlated with each other. For instance, technology development in transportation and communications opens new international markets for industrial and agricultural products trading and makes it easier to transfer products from country to country (Brad, 2015). The robots could be found in warehouses for carriage and storage purposes in product lines for assembling, packaging, transport, and arrangement of products (Srinivasan & Gebretstadk, 2011).

Technology development is ongoing and its effect is growing. Virtual reality, solar systems, robots, cyborg, and smartphones are changing the nature of human life than it was before a few decades (Lin, Abney, & Bekey, 2011). But on the other side, the negative impact is there. For instance, robots are increasingly replacing human in many jobs and the concern about future jobs and wages are consequently increasing. Acemoglu & Restrepo (2017) analyzed the impact of the increasing use of industrial robots in USA local labor markers in the interval between 1990 and 2007. They analyzed different tasks in the production industry, where the robots are competing with human labor. They found that robots reduced labor employment and wages. They claimed that each additional robot per thousand workers decreases wages by 0.25-0.5% and the employment to population ratio by about 0.18-0.34 percentage points. Whereas, Chui, Manyika, & Miremadi (2016) believed that automation will replace a few jobs in the coming decade. It will impact parts of whole occupations in different degrees based on the nature of the jobs in which they will be employed. They argued that 59% of manufacturing physical activities could be automated, such as product packaging, raw material filling into production lines, welding, and equipment maintenance, which are representing around 35% of overall workers' time. Furthermore, the aggregate employment levels in the warehouse industry are expected to grow to meet the expected growth in demand. Even though this growth may be mitigated by the increased use of advanced technologies, especially in e-commerce organizations, who are intensively deploying these technologies into their daily tasks, such as RFID tags applied to goods, auto-boxing, sensors, autonomous mobile robots, and auto-baggers. These technologies have the ability to reduce the time required to complete the tasks and some of them can alongside humans, such as autonomous mobile robots. The forecasts are pointing to labor reduction during the coming 10 years because of advanced technologies adoption (Gutelius & Theodore, 2019). Over and above, hiring the machines to perform the routine jobs will enable the workers to learn new capabilities that could let them gain higher wages and better-skilled jobs, such as maintaining and managing robots in the factories, which seems to be more stable than routine tasks (e.g. moving the boxes). Nevertheless, such specialized jobs are few when compared to routine shop-floor jobs. Furthermore, the organizations could outsource the robots with their maintenance services. This potential transition in the employment market raises questions for employers and policymakers about analyzing the best scenario that can support the workers during this transition. In fact, the proper implementation of such technologies in conjunction with better policies could reduce the proposed negative effect of technology on workers (Ghaffary, 2019). Oxford University had been examining 702 jobs to study the proposed impact of AI (i.e. machine at work) on human jobs. The study expected that 47% of jobs are at risk of disappearing. Meanwhile, the study deemed first-line mechanical supervisors, recreational therapists, occupational therapists, social health, installers, and repairers' professionals among occupations at lower risk of AI threat. A recent study by Manpower-Group suggests that 54% of the professionals in 2022 will require a new qualification and further training in how to manage and support new advanced technologies (Fernandez, 2019).

The ethical issues could be a major outcome of adopting such technologies. Palm & Hansson (2006) defined some aspects related to the ethical issues associated with the use of new technologies:

1. **Dissemination and use of information:** internet technology assisted in the dissemination of information facilitating crime, violence, and pornography. In addition to the ethical concerns about the unauthorized use of copyrighted and personal information.
2. **Impact on social contact patterns:** communication technology changed the way of contact between people, such as mobile phones and the internet. The electronic contact now is competing and substituting face-to-face contact, which reformulates the meaning of social interaction among humans.
3. **Privacy:** for instance, biometric authentication technology, camera control, and smart cards are offering continuous monitoring and tracking of peoples' daily activities. Which in turn created a critical ethical concern regarding personal privacy.

In the same context, some ethical issues, such as bodily integrity, control, security, and social inclusion have been raised with cyborg technologies (Park, 2014). McGee & Maguire (2007) claimed that the use of DBS could force individuals to behave while they are unconscious. And regarding the use of technological implants in criminals tracking and monitoring, they could learn how to avoid tracking by entering blind areas.

1.3 Research Objectives

Even though there is a wide range of studies on the acceptance of robot technologies in different fields, there is a lack of empirical researches that focuses on the use of them in healthcare services when compared to the services offered by human-beings. Meanwhile, the perception of humans to the proposed services that could be offered by cyborg is unknown. This gap or lack in studies can be understood because the proposed use of these technologies is still under the development stage. Which in turn, formulates the motivation for performing this research. The main aim of this research is to develop a model that can be used to identify the choice criteria among robot, cyborg, and human services. Which is in line with the question of this research:

What are the consumer choice criteria among robot, cyborg, and human services?

In addition, the proposed model could be considered as a starting point and a milestone for future researches and researchers who are interested in this domain. According to that, answering the research question will be through achieving the objectives of this research, which are consistent with the main aim. Also, the main focus of this research will be on healthcare services, especially for medical surgeries.

The first objective is related to the factors that influence cyborg acceptance as an entity in society. In fact, not much is known about the moral attitude of people toward the ratio between risk and benefits of using such technology and about their preferences, expectations, and needs. Meanwhile, the acceptance may be shifted from positive to a negative state, as the use of cyborg technologies will be shifted from therapy to enhancement purposes. Chapter 2 will discuss the innovation in this technology for therapy and enhancement applications. To be followed then with the related literature and some of the important previous studies about cyborg technology acceptance.

The second objective of this research is to investigate the robot acceptance. In this context, despite there are different previous studies regarding the acceptance of service robots. However, the actual response of consumers toward service robots is still under investigation and little attention has been paid to this context (Stock & Merkle, 2018). Therefore, this research will introduce and discuss different types of robots and related technologies in Chapter 3. Then it will review the related literature and some of the previous studies about robot acceptance in different applications, in order to develop a theoretical framework and methodology that can be used to explain and predict the factors that influence the acceptance of robot services.

The third objective is to investigate the intention to use human services. The decision-making process in choosing, purchasing, and using the services is important not only to the consumers but also to the organizations to understand how consumers will choose a specific product, especially when different alternatives are available (Bettman, Johnson, & Payne, 1991). And to understand this process, a general view of the service sector and human services, besides the consumer decision-making process will be discussed in Chapter 4.

After developing hypotheses and the model of this research in chapter 6, and to be more specific in the research focus area, this research will discuss the consumer behavior in emerging technologies within healthcare services in Chapter 7. This will include a general view of using robots and cyborg technologies in the healthcare sector and reviewing the related literature. Besides discussing patients' choice criteria of the human surgeons.

The fourth objective of this research is to measure end-user preferences among robot, cyborgs, and human services, and validate research model by analyzing survey data, which will be collected from participants through an online survey and will be analyzed using the partial least square structural equation modeling (PLS-SEM) technique. This technique utilizes a component-based approach and gives a simultaneous examination of the measurement model and the structural model. The measurement scales will be discussed in chapter 8, further explanation about PLS-SEM in Chapter 9, and the result will be shown in Chapter 10.

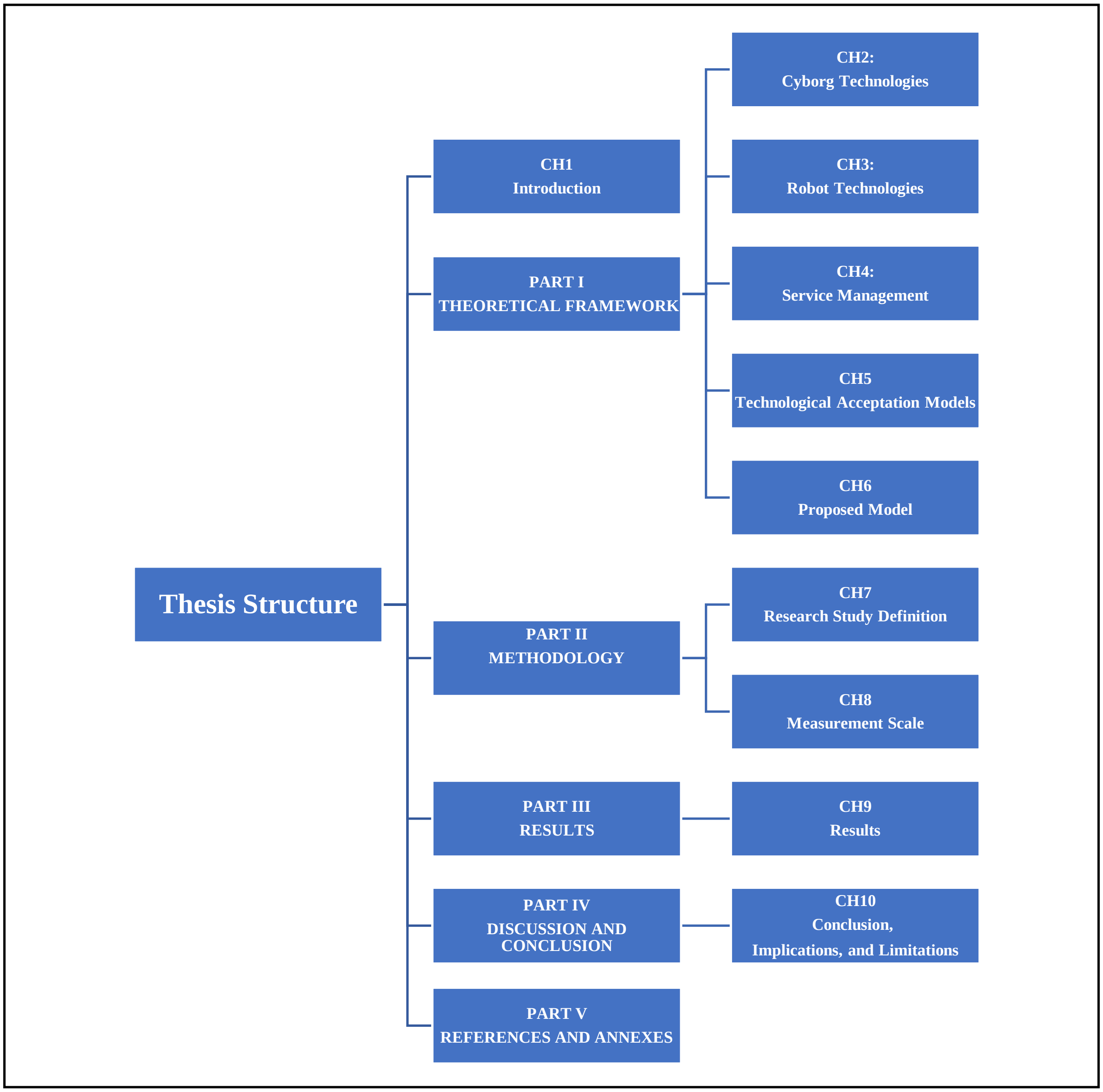
According to the model validation and analysis result, this research will be able to suggest some of the recommendations to the technology developers and services providers concerning consumer expectations toward the proposed services, such as expected features and abilities of robots and cyborg capabilities. Furthermore, the discussion of the human services' drawbacks will help the service providers to improve their services to meet consumers' expectations. This will represent the fifth objective of the current research. And the sixth objective will be related to giving directions to future researches, especially for the researchers who are interested in investigating the proposed use of robot and cyborg technologies. These recommendations will be discussed in Chapter 11: conclusion, implications, and limitations. Table 1.1 is summarizing the research aim and the objectives, and Figure 1.1 is illustrating the thesis structure.

It is important to mention that the terminologies superhuman, transhumanism, posthumanism, human enhancement, and cyborg will be used interchangeably across this research to represent the main term (i.e. cyborg).

Table 1.1 Research Aim and Objectives

Research Aim	Develop a model that can be used to identify the choice criteria among robot, cyborg, and human services.
Objective 1	Investigate and determine the factors that influence ***Cyborg*** acceptance as an entity in society.
Objective 2	Investigate and determine the factors that influence ***Robot*** acceptance as an entity in society.
Objective 3	Investigate and determine the factors that influence the intention to use ***Human*** services.
Objective 4	Measure end-user preferences among robot, cyborgs, and human services, and validate the research model.
Objective 5	Suggest recommendations to the technology developers and service providers concerning consumer expectations toward the proposed services.
Objective 6	Giving directions to future researches in robot and cyborg technologies acceptance context, especially in the service sector.

Figure 1.1 Thesis Structure



PART I: THEORETICAL FRAMEWORK

Chapter 2: Cyborg Technologies

2.1 Introduction

A belief in the ability of technology to increase innate human capacities, in addition to cultural assumptions about what is considered "incomplete," "normal," or "improved" leads to a variety of body-altering techniques that may not only restore functions; but also may exceed what is typically considered therapeutic intervention. Accordingly, a strong argument exists regarding the ability to enhance humans body according to particular needs or desires (Hogle, 2005). In this context, the enhancements are related to upgrading human capabilities, which opens a new type of researches concerning superhuman or what is called "Cyborg" (Parkhurst, 2012). Cyborg can be defined as a cognitively or bodily enhancement of human capabilities, and it can be called as a transhumanism. In general, transhumanism and technology convergence are directing the scientist's efforts toward enhancing human social skills, health, happiness, intelligence, and performance. In effect, cyborg technology has different forms, such as technological implants, brain-computer interfaces, externalization of cognitive functions, and neuronal prosthesis (Romportl, 2015).

Greguric (2014) pointed to four research areas affecting the development of human enhancement technologies: cognitive sciences, nanotechnologies, information technologies, and biotechnologies. Furthermore, the enhancements can be categorized into:

A. **Cognitive abilities enhancement**: such as infrared vision, memory enhancement, decision making, and sensory perception. These abilities could be achieved by using technological implants or wearables technology.
B. **Physical capabilities enhancement**: such as strength, stamina, and accuracy. These enhancements could be created by using bionic technology, genetic engineering, wearables technology, and pharmacology.

The technological implants can be defined as an electronic device that can be implanted into humans' body to improve their innate capabilities or for the restoration of lost functions (Pelegrín-Borondo, Reinares-Lara, & Olarte-Pascual, 2017). Moreover, there are different implantable devices in use for different purposes. Researchers and scientists claimed that brain-machine interaction will enable humans to log onto the Internet, to access different databases, to be able to talk new languages fluently and to help people with failing memories. It promises to make humans fundamentally different, by a radical change of their capabilities. Furthermore, humans will be able to control devices remotely by their thoughts (McGee & Maguire, 2007). In the following examples, this research will show some of the technological innovations that are related to cyborg technology.

2.2 Examples of Cyborg Technologies

2.2.1 Cochlear Implant (CI)

The first well-known implant device is the cochlear implant (CI), which is used to restore the hearing ability by replacing the hearing cells and translating the sounds into electrical impulses that stimulate the function of the auditory nerve (Jarrett, 2013). From a medical perspective, is the CI prosthesis? It could be considered as prosthesis, addition, replacement, extension, augmentation, or even enhancement. Nowadays, the term "cyborg" is used to compensate for the term "prosthesis" in academic researches and discussion forums about implants. Also, human engagement with the world is surely changed by the use of CI, and some CI users are introducing themselves as biotic or cyborg entities (Christie & Bloustien, 2010; Smith & Morra, 2006). As per Lee (2016), CI considered as a hearing aid, and it may become a part of human bodily functions, because the future may turn the use of it from therapy toward enhancement, to increase human hearing capabilities to become beyond the normality.

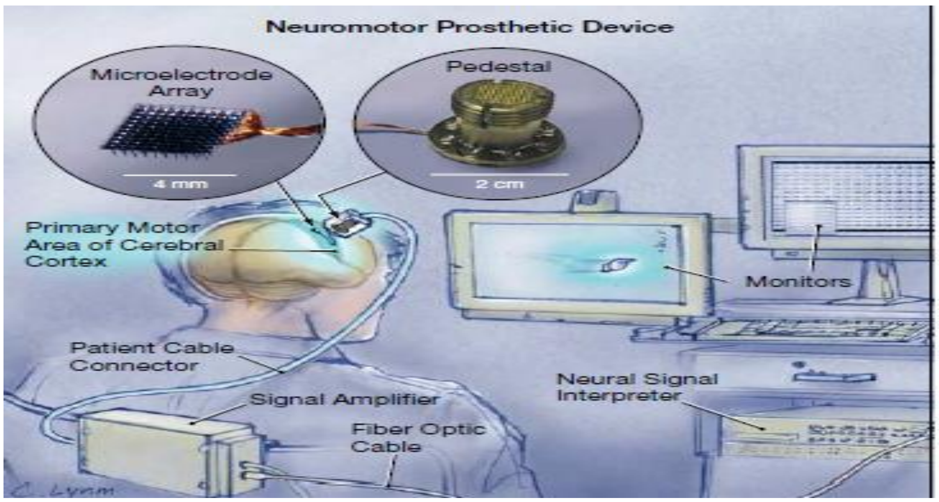
2.2.2 Neuromotor Prostheses (NMPs)

The purpose of using Neuromotor prostheses (NMPs) is to restore lost motor functions in paralyzed humans, through transferring signals related to the motion from the brain and around the damaged parts of the nervous system into external effectors (Figure 2.1). It works by using neural probe arrays implanted into the motor areas of the cerebral cortex for recording the activity of neurons, then computer algorithms translate the pattern of neural firing rates to produce output control signals to the external device, such as robotic arm, and depending on the user thoughts (Hochberg et al., 2006).

2.2.3 Deep Brain Stimulation (DBS)

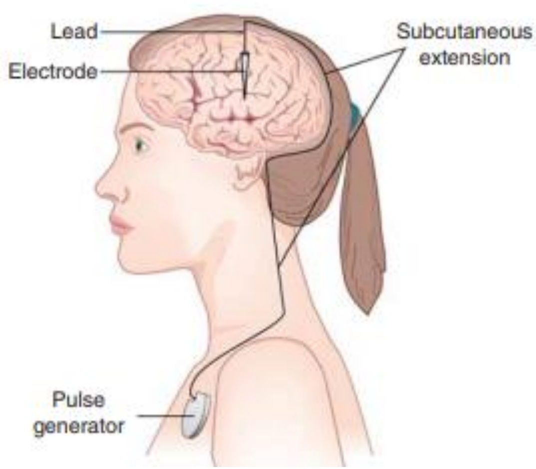
Deep Brain Stimulation (DBS) is the implantation of a neurostimulator, which is a medical device that sends electrical impulses into a specific targeted area of the brain, through two implanted electrodes for the treatment of movement and neuropsychiatric disorders (Figure 2.2). This technology offers therapeutic benefits for treatment-resistant disorders, such as Parkinson's disease, essential tremor, dystonia, chronic pain, major depression, and obsessive-compulsive disorder. Even though its effectiveness has been confirmed in treating some conditions, the potential side effects and serious complications still exist (Rabins et al., 2009).

Figure 2.1 NMPS



Source: (Friedrich, 2004, p.2179)

Figure 2.2 DBS

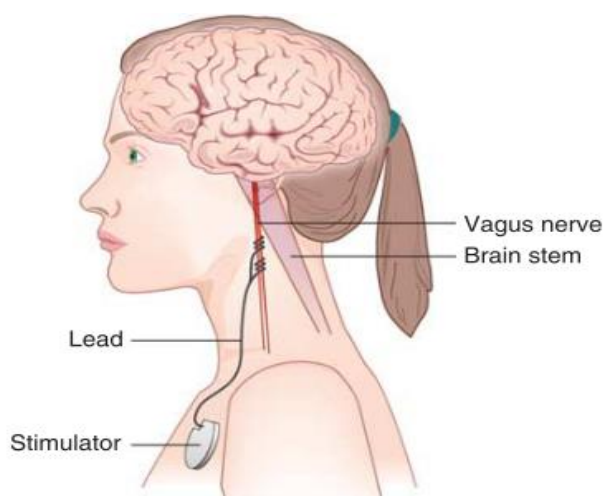


Source: (Rosa & Lisanby, 2014, p.109)

2.2.4 Neurofeedback

Neurofeedback is another type of human-machine interaction, where the brain activities are detected by devices like Electroencephalography (EEG) through placing sensors in the scalp to measure these activities. For instance, this principle is used for preventing epileptic attacks with the aid of Vagal Nerve Stimulation (VNS) (Duncan, 2006). The VNS (Figure 2.3) is a device implanted in the human body to stimulates the Vagus nerve by using electrical impulses. In reality, there is one Vagus nerve in each body's sides, running from the brainstem through the neck to the chest and abdomen. VNS technology is used to treat epilepsy when other treatments don’t work. Also, it can be used for hard-to-treat depression that hasn't responded to typical therapies. Researchers are trying to use VNS in the treatment of multiple sclerosis, headache, pain, and Alzheimer's disease. In Europe, noninvasive Vagus nerve stimulation devices, which don’t require surgical implantation, have been approved to treat epilepsy, depression, and pain. But haven’t been approved yet for use in the USA. Another VNS to be implanted in the right Vagus nerve is under study, which could be used in treating heart failure (Mayo Clinic, 2018). Also, the neurofeedback system was developed by the US army. Helmet attached with binoculars can alert soldiers to a danger that their brain detected it subconsciously, to react in a faster way. Technically, EEG can discover ‘neural signatures’ for target detection before the conscious mind becomes aware of a potential threat (Weinberger, 2007).

Figure 2.3 VNS



Source: (Rosa & Lisanby, 2014, p.108)

2.2.5 Biological Electrical Power Generation

Producing electrical power from biological sources has been achieved by implanting enzyme-modified electrodes into living lobsters, which resulting in biocatalytic oxidation of glucose and reduction of oxygen in the biofluid inside the lobster's body. For instance, this approach is used in the activation of the digital watch using "electrified" lobsters that are integrated with biofuel cells connected in series. Furthermore, by assembling implanted bioelectrodes with a fluidic device in series, and stimulating the human circulatory system to activate pacemaker. Finally, implantable devices, such as foot drop implants, gastric stimulators, spinal cord stimulators, cardiac defibrillators/pacemakers, insulin pumps, deep brain neurostimulators, and cochlear implants, can be powered by implanting biofuel cells and produce electrical energy from the human body (Vittie et al., 2013).

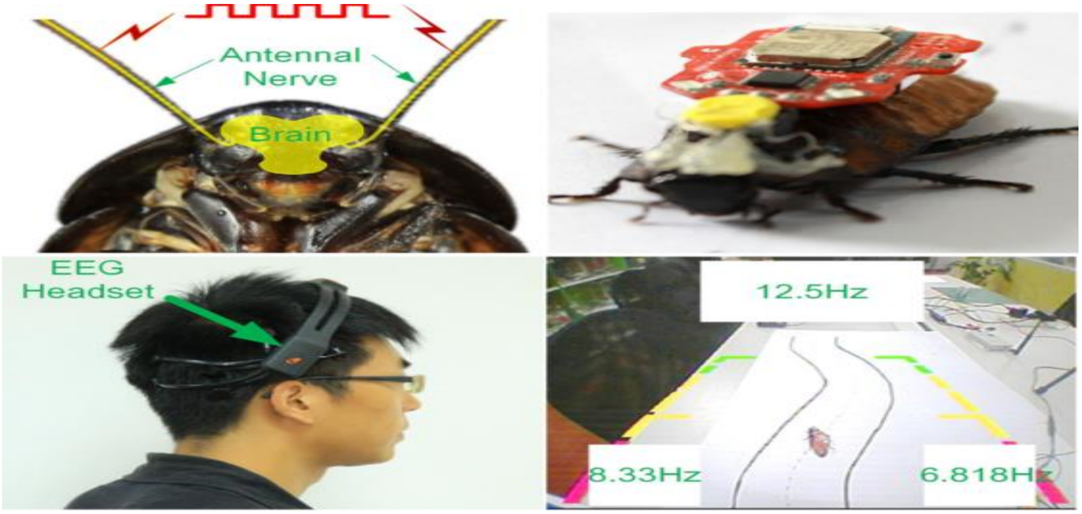
2.2.6 All-Chain-Wireless Brain-to-Brain System

Li and Zhang (2016) developed an all-chain-wireless Brain-To-Brain System (BTBS) that can control the motion of cyborg cockroach through the human brain (Figure 2.4). A portable microstimulator was integrated surgically into cyborg cockroach to produce invasive stimulation of an electrical nerve. A brain-computer interface (BCI) with Steady-State Visual Evoked Potential (SSVEP) was used to recognize human motion commands, and an optimization algorithm was suggested in SSVEP to improve the online performance of the BCI. A specific train of electrical impulses was triggered by microstimulator using BCI commands and sent through antenna nerve to stimulate the brain of cockroach via Bluetooth technology. The proposed BTBS enabled a practical and functional pathway to transfer the information from the human brain to the cockroach brain.

2.2.7 Retinal Stimulation

Retinal stimulation acts as a realistic solution for restoring vision to the blind people. Recently, different clinical experiments showed the ability of visual prostheses, especially retinal implants, to restore vision. A new concept of neuronal stimulation besides the traditional electrical stimulation, which is based on implanting metal electrodes in different areas of the visual path, is used to build the next generation of retinal implants. But, vision restoring technology is still under investigation and needs further cooperation between neuroscientists, material science, clinicians, and micro-fabrication sciences (Ghezzi, 2015).

Figure 2.4 BTBS

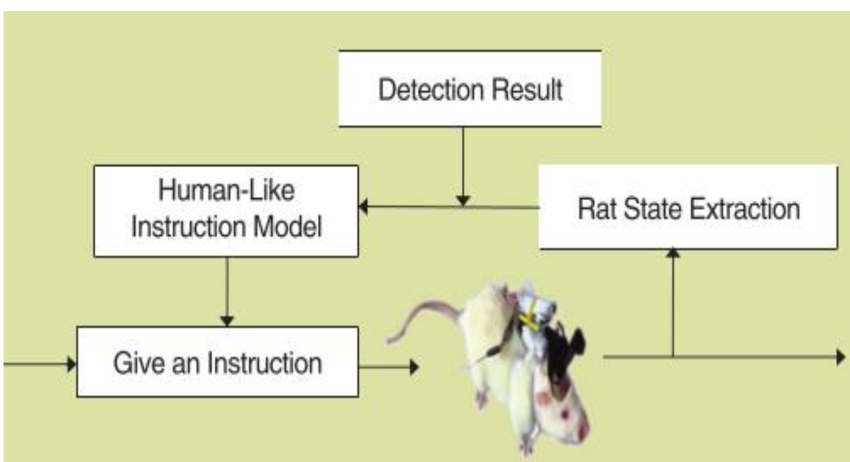


Source: (Li & Zhang, 2016, p.4)

2.2.8 Rat Cyborg

Wang et al. (2015) developed rat cyborg (Figure 2.5), which can detect faces and colored objects by using a miniature camera mounted on the rat back to capture the front views. Then, the captured videos are transferred by the wireless module into a computer with object detection/identification algorithms. This detection is used to activate stimulus, which can initiate the rat cyborg behavior based on a closed-loop model. These comprehensive experiments confirmed that the rat cyborg can execute visual cue-guided automatic navigation.

Figure 2.5 Closed-Loop Model

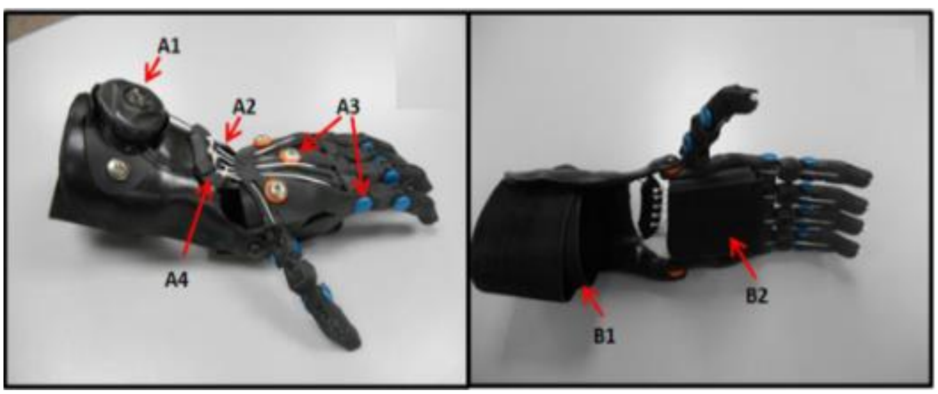


Source: (Wang et al., 2015, p.46)

2.2.9 3D-Printed Prosthetic

The demands on prosthetic devices for children and adults are increasing vastly due to the increased number of accidents and congenital upper-limb deficiencies. (Bethge, Groote, Giustini, & Gutenbrunner, 2014). These prosthetic devices should be cost-effective, easy to use, can be replaced easily, useful, and attractive (Resnik, 2011). The 3D printed prosthetic was developed to meet those requirements (Figure 2.6), which called “Cyborg Beast”. By placing elastic cords inside the dorsal part of the fingers to create a flexible finger extension. The palmar surface of each finger is fitted with non-elastic cords to produce 20^{o}-30^{o} wrist flexion. The result is a fist that can grasp and flex fingers toward the palm. The cost of this prosthetic components (i.e. PLA plastic, Acrylonitrile Butadiene Styrene (ABS), screws, nylon cords, elastic cords, foam, skin sock, and Velcro) is around 50 USD, and most of them can be ordered online (Zuniga et al., 2015).

Figure 2.6 Cyborg Beast



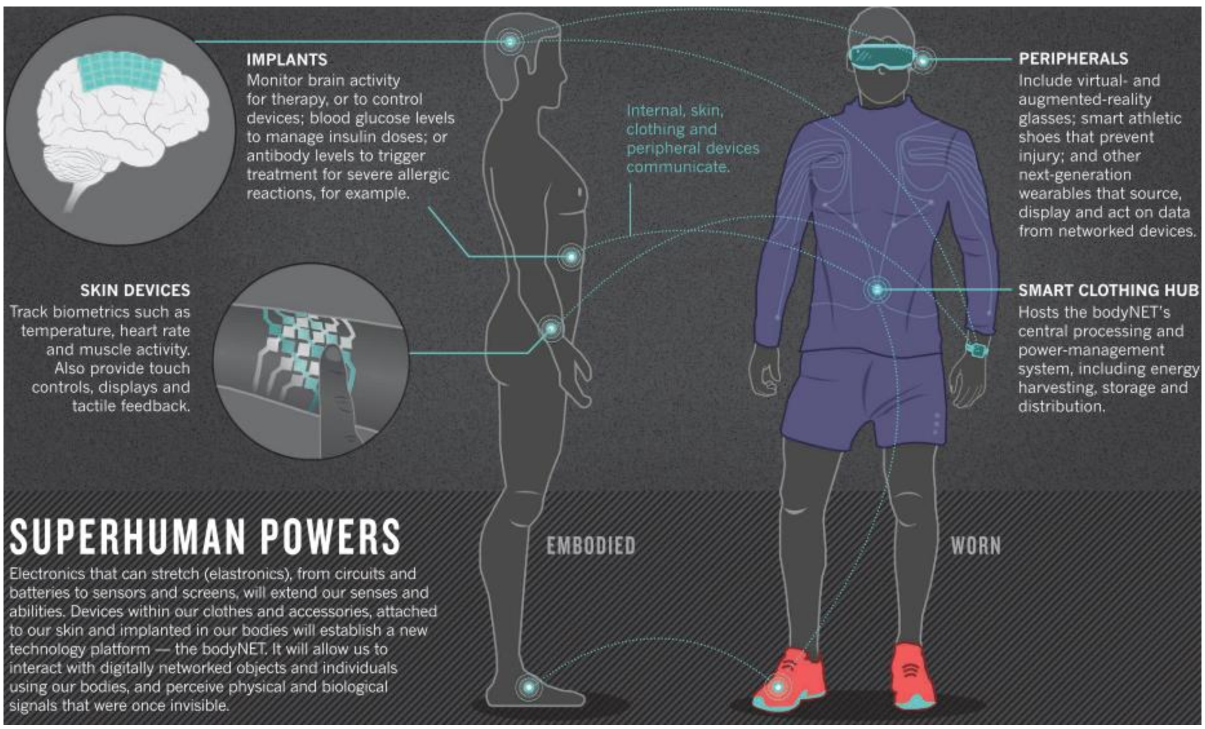
Source: (Zuniga et al., 2015, p.2)

2.2.10 BodyNET

BodyNET (Figure 2.7) is a wireless Body Network Sensors (BNS) contain a set of sensor nodes that communicate with each other and with smart devices (Yang, 2014). BNS can be implanted into the human body or used as a wearable device. The nodes contain a wireless transmitter, a computer processor, a storage unit, and other features that could be customized based on the application. It can measure body temperature, brain and muscle activities, heart rate, and other biomarkers. Then it sends these readings to the connected device (smartphones or IoT devices). This technology can be used to monitor human health, e-fitness, e-sport, monitoring the safety of the factory workers (e-factory), monitoring human emotional states (e-social), and so on

(Fortino & Yang, 2016). Actually, BodyNET technology is still under development, and there is still much to do. The labs around the world are working on the development of BodyNET components. The core component in this innovation is the elastic-electronics (i.e. elastronics), which is about creating devices that can be stretched without getting damaged and made from thin plastic circuits, can respond to temperature, humidity, touch, pressure, light, chemical and biological signals. Presumably, elastronics technology and biological electrical power Generation technology (i.e. superhuman power) are leading the future of wearables and implants technologies (Chu, Burnett, Chung, & Bao, 2017).

Figure 2.7 BodyNET

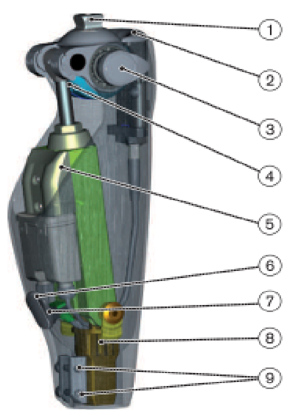


Source: (Chu et al., 2017, p.330)

2.2.11 Microprocessor Knee

The microprocessor prosthetic knees have been used to replace the mechanical ones. They are offering lightweight and small size when compared to the mechanical knees. They have lithium batteries that can last for 40 hours, the leg can be switched to different motion modes by remote control or smartphone application, it can reduce walking effort, and most of them can hold up to 125 Kg (Ernst, Altenburg, Bellmann, & Schmalz, 2017). A set of sensors is used to capture real-time data and send it to the microprocessor to control the stance and swing of the leg movement. These prosthetics are offering the closest gait for the normal ones when compared to other prosthetic types. And they can be adjusted automatically, which will reduce the compensated effort that is needed from the other limb (Segal et al., 2006). For instance, in C-leg (Figure 2.8), the microprocessor uses the information from the sensor to control the hydraulic unit. Where the sensors' data are updated 100 times per second, which makes the unit able to adapt the current motion in a real-time manner. Also, the motion pattern of this unit can be adjusted by an application installed into the user smartphone (Ottobocku, 2018).

Figure 2.8 Prosthetic Leg



1. Proximal pyramid adapter
2. LED (blue) as indicator for the Bluetooth connection
3. Battery and cover caps
4. Optional flexion stop (8°)
5. Hydraulic unit
6. Charging receptacle cover
7. Charging receptacle
8. Pylon stop
9. Distal tube clamp screws

Source: (Ottobocku, 2018)

2.3 Literature Review of Cyborg Technologies

When cyborg technologies will be established, people's understanding of technology design and use must be shifted to perceive the differences between traditional technology and new technology applications (Britton & Semaan, 2017). In addition to that, the development of these technologies is important for the future of neural prosthetic inventions. In fact, not much is known about the moral attitude of people towards the ratio between risk and benefits of using such technology and about their preferences, expectations, and needs. Furthermore, the ethical issues related to the associated risk with these technologies and their limits are an important topic that has to be discussed. Meanwhile, the acceptance could be shifted from positive to negative state, as the use will be shifted from therapy to enhancement purposes. For instance, CI's could be considered a therapy device if the user is deaf. If not, it would be considered an enhancement. The successes of these technologies will depend on the offered benefits and people's perception of these benefits (Schicktanz, Amelung, & Rieger, 2015).

The technological implants to restore physical functions and physical implants to increase seductive strength are already accepted by society (Pelegrín-Borondo, Reinares-Lara, et al., 2017). And, few studies have been conducted to investigate the acceptance of implants for capabilities enhancement to become a cyborg (Olarte-Pascual et al., 2015; Pelegrín-Borondo et al., 2018, 2016; Pelegrin-Borondo et al., 2017; Pelegrín-Borondo, Reinares-Lara, et al., 2017; Reinares-Lara et al., 2018, 2016). On the other side, nothing is known about the consumers' perception of the services that could be offered by cyborgs once they get hired in the service settings. Accordingly, this research is going to investigate the acceptance of cyborgs in healthcare services, especially as a surgeon and when compared to the robot and human surgeons.

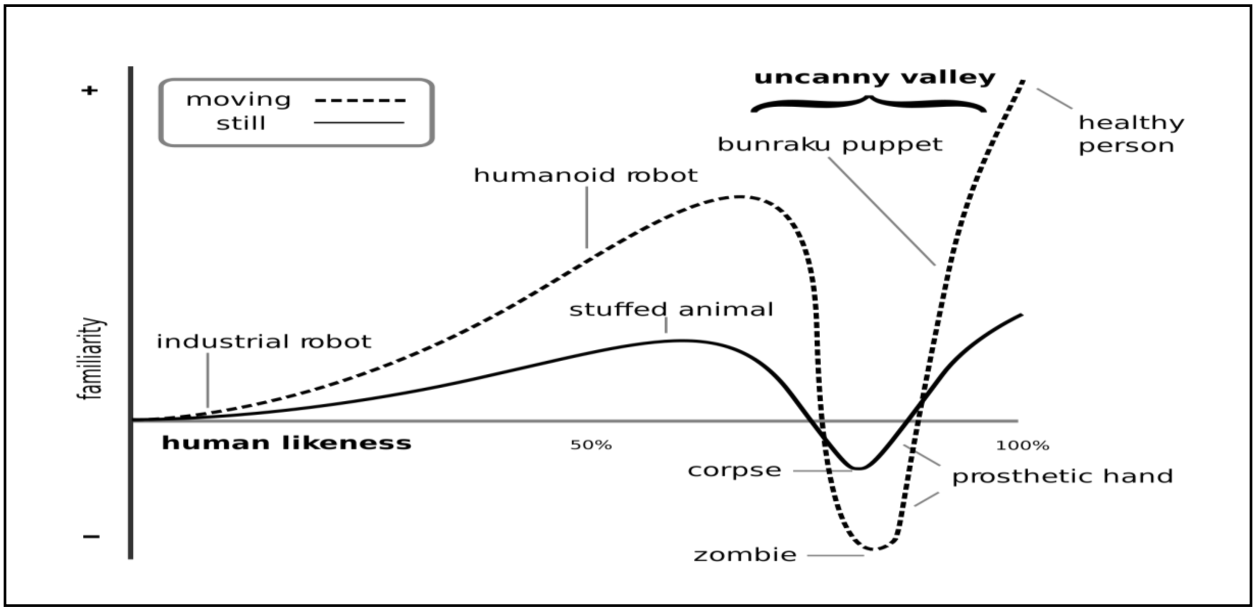
In terms of technology, the enhancement could be visible (i.e. wearables) or invisible (i.e. implants). Moreover, it could be organic, mechanical, or a combination of both of them. In Fact, using the technological implants to create a cyborg will keep the enhanced human to look like a normal one. This means and from the appearance perspective, the enhanced humans will avoid the negative social response that could be associated with their abnormal looks (West, 2016). Consequently, the acceptance of cyborg could be unlike the machines' acceptance (e.g. robot), because the cyborg is still a human with enhanced capabilities that are beyond the normality. However, to make a complete picture, it is necessary to study cyborg acceptance from both perspectives: as a machine and as a human, since in both cases (i.e. implants and wearables), the technology is the major part of human's body.

Even though the cyborg technology is still in its development stage, there are some examples and attempts to implement cyborg technology and as mentioned in the previous examples. For instance, "Neil Harbisson" has color blindness. Neil now can hear the colors through a camera placed on the front of his face. The camera captures the colors as visual signals and sends them to a chip located on the back of his head. Then the chip converts the visual signals into sound waves. And through these sounds, his brain can distinguish between different colors. This "Eyeborg" gives Neil the ability to recognize colors that can be perceived by normal humans and the colors that laid beyond human vision ability. Neil has been considered as the first official cyborg because his Eyeborg is shown in his current passport photo (Parkhurst, 2012). In fact, Neil's journey was not easy with that Eyeborg. He mentioned through an interview with BBC News that two police officers attacked him when he was visiting Paris. They thought he was filming them, and even after he told them it is for hearing sounds, they thought he was laughing on them and they crashed his Eyeborg. Furthermore, he spent a lot of time to convince the UK authorities to accept his new photo wearing the Eyeborg to be used in his new passport. Neil's journey has pointed out the importance of technological awareness about cyborg technology to avoid the expected social resistance of the potential cyborg entities (BBC, 2012). Actually, the literature showed how technological awareness can reduce the possibility of rejecting new technologies (Mutahar, Daud, Ramayah, Isaac, & Aldholay, 2018). In this context, special programs and campaigns could be required to increase public awareness regarding the new technologies in terms of their potential benefits for humanity (Kardooni, Yusoff, & Kari, 2016).

Normally, people formulate their impressions about an individual or group based on the traits of that individual or group. Traits help people to understand and expect other's behavior and formulate their behavior (Tausch, Kenworthy, & Hewstone, 2007). In addition to that, when people interact with others, they start looking to the match between their goals and other’s goals (Warmth), and if they can follow these goals (Competence). Warmth and competence are representing the universal dimensions of social cognition, and they are shaping people’s emotions and behaviors (Fiske, Cuddy, Glick, & Xu, 2002). Peeters and Czapinski (1990) pointed out the self-profitability, which corresponds to competence. They suggested that behaviors and traits are associated with personal outcomes. For instance, intelligent persons will benefit themselves. On the contrary, nonintelligent ones will harm themselves, not the others. On the other hand, for other-profitability dimensions, which correspond to warmth, traits and behaviors are related to interpersonal outcomes. This means, when people interact with helpful and honest person, they will benefit from these behaviors and traits.

In general, humans will start to use the perceptual cues and former experiences to classify an object and to effectively expect its behavior. For instance, while interacting with the cyborg, a human could recognize the abnormality of the other human from the physical structure (wearables) or through the behavior (implants). This stage is very important to avoid falling in “Uncanny Valley”, in which the human will feel with unfamiliarity while interacting with human-like objects (Stein & Ohler, 2017). Originally, uncanny valley theory was introduced by Mori (1970) to propose the relation between human-likeness and familiarity while dealing with industrial robots. The theory proposed that, at some point (First Peak), maximum familiarity will be achieved once the robots become human-like in terms of behavior and appearance. Furthermore, the motion will enhance familiarity perception. However, the author pointed out the feel of strangeness, which can drop familiarity toward the negative portion. This negative portion of the familiarity graph is representing the "Uncanny Valley" (Figure 2.9). A critical point had been mentioned by the author regarding the prosthetic hand, which is representing one of the cyborg forms. He mentioned that, as the enhanced prosthetic hand looks like normal ones, humans will perceive the familiarity with the cyborg. But, once humans figure out the abnormality of this hand, the familiarity curve could drop to the uncanny valley, and humans will feel with eeriness.

Figure 2.9 Uncanny Valley Theory



Source: (Mori, 1970, p.33)

Some authors in the literature refer to the problem of trust when humans meet strangers. They mentioned the role of facial expressions in affecting trust behavior. Scharlemann, Eckel, Kacelnik, and Wilson (2001) investigated the relationship between facial characteristics and trust while interacting with others. Their study claimed that facial expressions (e.g. smile) can stimulate trust behavior. Additionally, for life-like agents, trustworthiness could be achieved by enhancing their competence (Mulken, André, & Müller, 1999). In the same context, empathy and emotions can overcome the uncanniness outcomes. Emotions have been considered as a way to distinguish humans from objects and machines. Furthermore, the ability to express basic emotions could be proof of humanity (Heisele, Serre, Pontil, Vetter, & Poggio, 2002). In fact, the idea is about the mismatch between human expectations and perception to avoid uncanniness. For instance, the ability of robots to express emotions may lead to the uncanny valley, which in turn could produce eeriness feeling, because robots then will become beyond a machine. However, their ability to experience and detect emotions without expressing it could keep them in the same area at the First Peak (Koschate, Potter, Bremner, & Levine, 2016). Moreover, as the proposed relation between humans and cyborgs will involve direct interaction, it is essential to investigate the impact of anxiety emotion on the interaction. Indeed, the expected anxiety is a reflection of the abnormality and superpower associated with cyborg technology. Factually, anxiety problem isn’t related to the technology itself, rather than it is an emergence of this negative feeling while interacting with it (Oh et al., 2017). However, changing the attention toward the benefits of the technology could help in reducing the associated anxiety during the interaction with it (Reinares-Lara et al., 2016). Meanwhile, some studies claimed that anxiety isn’t a significant determinant of the intention toward the new technologies (Pelegrín-Borondo, Reinares-Lara, et al., 2017; Venkatesh, Morris, Davis, & Davis, 2003).

It could be worthen to stimulate the acceptance of cyborg throughout the acceptance of human-like agents and the acceptance of being cyborg because it is still an outcome of the technological innovations. In this context, the acceptance of such technologies includes theories about technology acceptance, such as Technology Acceptance Model (TAM1) for Davis (1985) and its extensions TAM2 (Venkatesh & Davis, 2000) and TAM3 (Venkatesh & Bala, 2008), the Unified Theory of Acceptance and Use of Technology (UTAUT1) for Venkatesh et al. (2003) and its extension UTAUT2 (Venkatesh, Thong, & Xu, 2012), and the Cognitive-Affective-Normative Model (CAN) for Pelegrín-Borondo et al. (2016), which has been developed to study the acceptance of being a cyborg. The perceived ease of use is one of TAM constructs that represents the effort needed to use a specific system. The second construct of the TAM model is perceived usefulness, which is related to the benefits associated with the use of any technology (Davis, 1985; Heijden, 2004). Performance expectancy, which corresponds to perceived usefulness, is related to the individuals' beliefs about the system's ability to improve their job performance. And effort expectancy, which corresponds to perceived ease of use, is related to the simplicity of using the system (Venkatesh et al., 2003). Human needs to perceive the usefulness of cyborg in terms of its superiority in performance when compared, for instance, to humans and robots. It can stimulate the acceptance of dealing with cyborg if human find it better than the other options, or stimulate the rejection if there are no differences in terms of performance and outcomes. But it is important also to consider the possibility of the low effect of these two constructs in the initial investigation of cyborg acceptance, since the technology is still in its novelty stage (Pelegrín-Borondo, Reinares-Lara, et al., 2017).

Since individuals are members of their social entities, other member's opinions and advice toward any behavior or decision could make a difference and could direct that behavior or decision. Therefore, it makes sense to investigate the effect of social influence while studying the acceptance of new technology (Ajzen, 1991). In fact, this side was studied in technology acceptance literature and it is one of the main constructs in technology acceptance models. The social influence was introduced by the Theory of Reasoned Action (TRA) for Fishbein and Ajzen (1975) and the Theory of Planned Behavior (TPB) for Ajzen (1991). For example, the literature showed the significant impact of this construct on the acceptance of new technologies (Davis, 1989; Venkatesh, 2000). As well, its impact on the acceptance of Nanoimplants (Pelegrín-Borondo, Juaneda-Ayensa, González-Menorca, & González-Menorca, 2015; Pelegrín-Borondo et al., 2016; Pelegrín-Borondo, Reinares-Lara, et al., 2017; Reinares-Lara et al., 2018, 2016), breast augmentation for young women (Moser & Aiken, 2011) and on the acceptance of virtual consumer integration (Füller, Faullant, & Matzler, 2010).

In Cognitive-Affective-Normative (CAN) model, Pelegrín-Borondo et al. (2016) used the emotional dimensions: positive and negative emotions. However, there is some degree of consensus that the arousal and pleasure emotional dimensions are the most adequate dimensions to analyze the emotional response of an individual to a stimulus (Pelegrín-Borondo et al., 2015). The level of emotional pleasure and emotional arousal are the most supported emotional dimensions by literature (Cohen, Pham, & Andrade, 2008; Pelegrín-Borondo et al., 2015; Russell, 1980, 2003). In this sense, Mehrabian and Russell (1974) and Russell and Mehrabian (1977) suggested that you can measure what a person is feeling by employing a limited number of emotional dimensions. They proposed a scale with three dimensions: pleasure, arousal, and dominance (PAD). Eroglu, Machleit, and Davis (2001) recommended using arousal and pleasure only, and without the dominance dimension. They claimed that these two dimensions can represent the range of emotions that emerged in response to environmental stimuli and based on Russell's (1979) recommendation. Pleasure is related to a person's state of feeling of goodness, happiness, joyfulness, or contentedness in a certain situation. And, arousal is about a person’s state of feeling with excitement, alert, stimulation, wakefulness, or activeness in a certain situation (Das, 2013; Mehrabian & Russell, 1974). Positive arousal and pleasure emotions can allow humans to feel with optimism while choosing their plans and goals. In fact, arousal could be seen as preparation toward actions (Russell, 2003). Also, pleasure can affect consumer behavior toward a successful choice of a specific service or/and product. Moreover, while using a specific service, consumers may develop positive or negative emotions. The positive ones are important for the future behavior of consumers (Pappas, Giannakos, & Chrissikopoulos, 2013). Furthermore, they are considered important in directing the attitude of consumers toward new technologies, and they can enhance the predictive power of the technology acceptance models (Kulviwat, Bruner, Kumar, Nasco, & Clark, 2007).

The interactivity, autonomy, and personification are significant in the virtual agent to be realistic and to get succeed in the interaction with human-being (Kang & Tan, 2013). Autonomy is related to acting independently without anyone's control (Wang & Mckenzie, 1998). It is required for humans to perceive the cyborgs as an autonomous entity to capture their human-like side. While, interactivity is one of the human-like characteristics. It includes facial expressions, conversational abilities, and the ability to utilize body language. Moreover, personification is related to agent personality and emotions, which have to be in the human-like boundaries. The personality is significant to differentiate among people. And emotions are integrated into personal life, which could have a significant impact on people's perceptions, behaviors, beliefs, and cognitive processes (Kasap & Magnenat, 2007).

2.4 Studies about Cyborg Technologies

It is still unclear how people will perceive the term “Cyborg”, especially with the limited studies about accepting to become cyborg, and almost nothing is known about accepting cyborg as an entity in society. This is understood because the technology itself is in the novelty stage, and limited options are available in the market. For instance, insideable technologies are promising to make a difference in treatment and enhancement sides. Recently, VeriChip, which is used for biometrical identification, is already in the market and can be used in identity proof, storing data and there is a potential use for electronic payments and storage for electronic health data (Schmeh, 2013). In addition to that, cosmetic implant surgeries, like breast augmentation, and treatment implants, such as pacemakers, are already accepted in society. In this context, Olarte et al. (2015) studied the acceptance of technological implants to increase innate human capacities (T3IC). The results pointed to the readiness of part of society to accept these technologies. The applications of these implants in which people are interested to acquire could stimulate the acceptance toward it (e.g. implants for delay age, increase memory, or enhance computational abilities).

Currently, human body boundaries need to be revised and formulated again, to be able to distinguish between what is human and what is non-human. Consequently, an ethical question has been raised regarding safety, risk, and proposed side effects that could be associated with using such technologies. From an ethical perspective, technological implants for therapy use are accepted. While, it is still unclear for enhancement applications, despite what some authors mentioned about the critical need for reformulating the meaning of ethics, in terms of moral judgments, so that it could be applied to this type of technology and its applications (Schermer, 2009). In this context, Pelegrín-Borondo et al. (2018) investigated the effect of ethics on the acceptance of brain implants. The authors mentioned the ethical problem which is covering different areas, such as personal security and privacy and its impact on personal identity. The study implemented the ethical construct into the CAN model, to investigate its moderating influence on the acceptance of brain implants for increasing capacities. Even though results didn't prove the moderating effect of the ethical side on implants acceptance, it explained the intention differences in using them.

The dilemma of these technologies and across all the related studies was in how to differentiate between therapy and enhancement use. Although it seems easy to find out the differences, they are overlapping in some cases, and the technology itself isn't innate or natural for both cases. Parkhurst (2012) discussed this dilemma and mentioned how cosmetic surgeries are now deemed in some societies as a therapy, critical for social belongingness and mental health, and a sign of equity. Furthermore, skin lightening in the Arabian Peninsula is considered as a need to restore the natural state of the skin, not as an enhancement. On the other side, cosmetic surgeries in Brazil and Arabian Peninsula considered as therapy, while pacemakers and transplants in Kansas City are not. Also, he mentioned the religious views to these technologies, where some religions may consider altering the body is completely forbidden, especially for non-medical use (e.g. tattoo is prohibited in some religions). Which is pointed out to the importance of the cultural dimension while dealing with such technologies. Consequently, studying the acceptance of cyborg technology should consider the cultural differences during the investigation. For instance, integrating the ethical dimension within the CAN model and implementing it in different countries is required to be able to generalize the model results, as the ethical aspects are inherently cultural (Reinares-Lara et al., 2018).

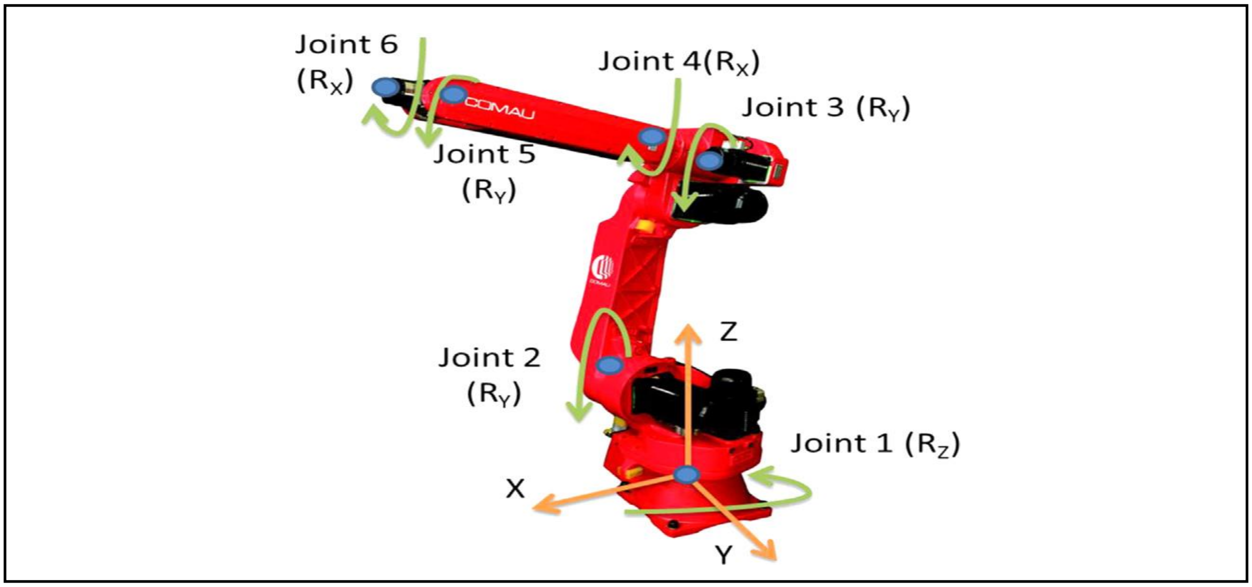
As mentioned before, cyborg technology could be wearable or implantable for both therapy and enhancement use. In the healthcare context, the wearable technologies market is trending and the expected revenue may reach up to 22.9 $ million by 2020. In terms of its applications in healthcare, it is used for fitness monitoring, such as 360 Kids Guardian, Fitbit, and Jawbone devices, which are used to monitor users walked steps and distances, burned calories, diet, and so on. And it is used for medical purposes and has been designed specifically for some diseases, such as cancer and diabetes. Gao, Li, and Luo (2015) studied the acceptance of healthcare wearable technology. The data were collected from participants who are already using these technologies. The authors mentioned three significant factors related to the intention to use wearable technologies in terms of privacy, healthcare, and technology perspectives. Furthermore, their results suggested that the importance of these factors is depending on its application (i.e. for medical or fitness applications). For instance, social influence is significantly important for fitness wearables. However, performance expectancy is one of the important determinants of acceptance of medical wearables.

Chapter 3: Robot Technologies

3.1 Introduction

Before a century, robots' ability for autonomous mobility and to perform a set of tasks had been captured by writers' imaginations. While recently, robots have emerged from the pages of science fiction novels into the real world (Graetz & Michaels, 2015). Different types of robots were developed in the past few decades, such as industrial, mobile, educational, collaborative, and service robots (Park & Pobil, 2013). Industrial robot (Figure 3.1) is defined as "a reprogrammable and automatically controlled robot that has the ability to perform a multipurpose manipulation with three or more programmable axes. It could be fixed or mobile and used in industrial automation applications (ISO, 2012).

Figure 3.1 Industrial Robot



Source: (Kaltsoukalas, Makris, & Chryssolouris, 2015, p.67)

Service robots (Figure 3.2) are set of mobile robots, designed to work in populated environments, such as hospitals, offices, restaurants, universities, museums, and homes. They are developed to perform different tasks, like cleaning, education, entertainment, and eldercare. Likewise, there are some of the autonomous and intelligent robots that are in use for home assistant tasks (Bennewitz, 2004).

Figure 3.2 Service Robot for Eldercare

Source: (Saaskilahti, Kangaskorte, Pieska, Jauhiainen, & Luimula, 2012, p.561)

Educational robots (Figure 3.3) are used in language learning, teaching assistant, development of social skills, and so on. They have the social ability to interact with students (Cheng, Sun, & Chen, 2018).

Figure 3.3 Educational Robot

Source: (Cheng et al., 2018, p.415)

On the other hand, AI and ML technologies are embedded in the robots' technology, and the vast development in both of them enables new features and improvements in robot design. For example, motion control, vision, grasping, and understanding data patterns are some of AI and ML inventions, which are implemented in robots (Robotics Online, 2018). Regarding AI, it is considered as a branch of Information Technology (IT), which is studying human intelligence behaviors (e.g. recognition, problem-solving, learning, perception, language use, creativity and manipulation of symbols) to produce models that can be used in creating computer programs that have the ability to simulate human intelligence. These programs can be used for different purposes, such as voice recognition, shape recognition, theorem proving, games running, language translation, music composition, medical diagnosis formation, and expertise formation (Furmankiewicz et al., 2014). For instance, people don't move at random through their environment but they ordinarily follow a particular path or motion patterns and based on their intentions. The ability of mobile service robots to know these patterns will enable them to keep track of people motion and enhance their behavior (Bennewitz, Burgard, & Thrun, 2002).

ML is related to build computers that can learn from experience. And it represents a combination of different sciences, including computer science, statistics, data science, and AI. Recently, the development of ML is driven by new learning algorithms, big-data, and inexpensive computation systems (Jordan & Mitchell, 2015). For example, in the healthcare sector, ML is considered a flexible and powerful instrument that can be used to resolve and predict results from clinical and biological information. Its models have the power to improve the efficiency of healthcare in different ways, such as in implementing diagnostic models that can be used in risk stratification, in the medical examination, and therapy recommendations (Gui & Chan, 2017). Furthermore, various ML methods have been successfully utilized in emotional recognition to predict individuals' emotional state, by using a set of physiological features as a reference. In this context, the robots need to be able to capture the companion emotional state. Realizing emotional status from physiological cues is an efficient method for achieving successful human-robot interaction (Liu, Rani, & Sarkar, 2005).

In the following sections, this research will discuss in more detail the AI, ML, and Bots as examples of robot technology innovations. Then, this research will discuss the related literature review and previous studies that are related to robot technology acceptance.

3.2 Examples of Robot Technologies

3.2.1 Artificial Intelligence (AI)

The term AI was initiated in the forties of the last century to introduce a computer system that can imitate human intelligence and even to become more intelligent than humans. Nowadays, AI can perform complex tasks that are considered hard for humans to perform, in faster and accurate ways (Garrido, 2010). McCarthy (1956) was introduced the term AI in the Dartmouth conference, which was considered the year of AI birth. From that year, different works have been established in the context of AI development. In 1958, McCarthy invented the "LISP" (i.e. List Processor) programing language and it was introduced to the public in 1960. It was designed to manipulate symbolic information (McCarthy, 1978).

Bobrow (1964) showed that computers can solve algebra problems by understanding natural language. He introduced "STUDENT" using LISP, which can accept a wide set of algebra problems expressed by a subset of the English language. It can find a solution to a large group of problems and it can employ a store of common information, which isn't specified for any single problem. In addition to its ability to make assumptions regarding ambiguity interpretation in the solved problem framing. Furthermore, when the STUDENT uses this information or makes any assumption, it will report them to the user. Moreover, it transforms the input sentences into equations to form the semantic base of the STUDENT. Then, it will try to solve these equations and it will answer in English if it gets success in finding the solution. If not, it will request more information from the user. STUDENT has been considered as the first step in utilizing natural language in communication with computers.

Weizenbaum (1976) introduced ELIZA in MIT Computer Science and AI Laboratory, which is a natural language processing computer program, and it was considered as the first Chatbot. Based on handmade scripts, ELIZA can communicate with humans. For instance, the DOCTOR is a version of ELIZA that imitate Rogerian psychotherapist. It is using pattern matching to response to the chat, rather than understanding the conversation. As per Weizenbaum (1976), DOCTOR became well known, and some psychiatrists believed in the ability of this Chatbot to grow and to become almost a complete automatic form of psychotherapy. Moreover, he considered the relation between users and DOCTOR became more emotional. He suggested drawing more attention to the emotional aspects of the human-computer relationship by enhancing computer capabilities to imitate the human behavior. Figure 3.4 shows an example of a conversation between the ELIZA DOCTOR and a human.

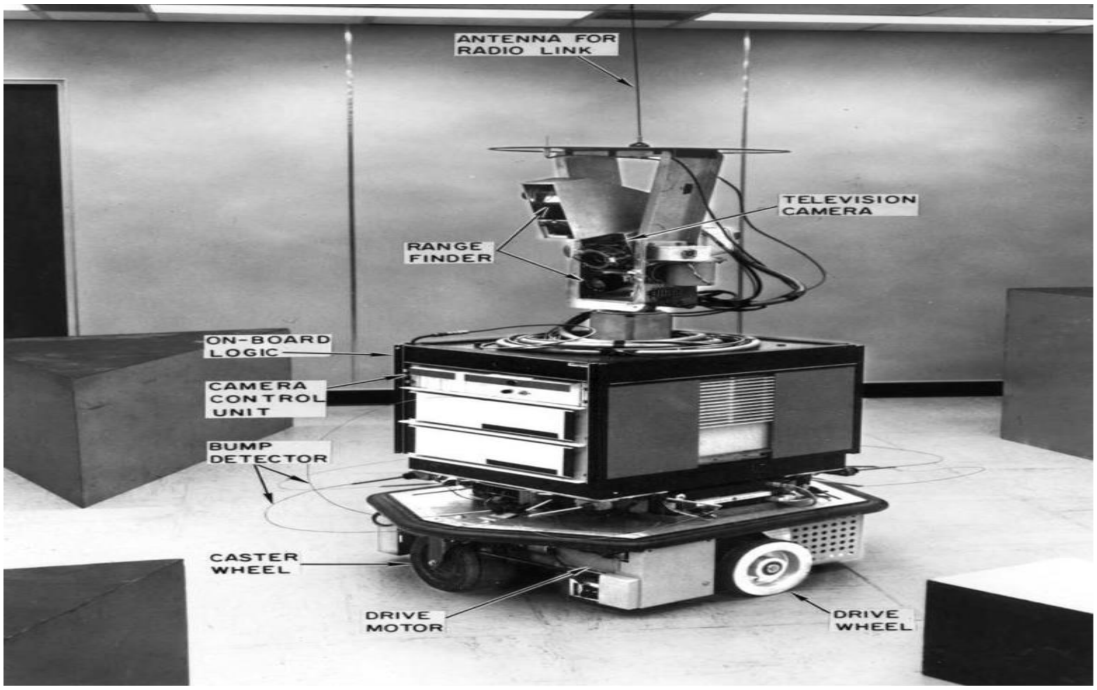
Figure 3.4 ELIZA DOCTOR Conversation with a Human

ELIZA: Is something troubling you?
Person: Men are all alike.
ELIZA: What is the connection, do you suppose?
Person: They're always bugging us about something or other.
ELIZA: Can you think of a specific example?
Person: Well, my boyfriend made me come here.
ELIZA: Is it important to you that your boyfriend made you come here?
Person: He says I'm depressed much of the time.
ELIZA: I am sorry to hear that you're depressed.
Person: It's true. I am unhappy.
ELIZA: Can you explain what made you unhappy?

Source: (Weizenbaum, 1976, p.3)

SHAKEY Robot (Figure 3.5) was introduced by Stanford Research Institute (SRI), which was the first mobile robot system. Two versions of this robot were developed. The first one was introduced in 1969, a mobile vehicle with sensors and cameras controlled by a computer. And the second one was launched in 1971 with enhanced performance. The developers improved the program and used digital equipment to control the robot. It was the first project combining physical action and logical reasoning. The robot programming was done in LIPS, and the software was using the Stanford Research Institute Problem Solver (STRIPS) planner as the main planning component. It was programmed to perform a limited number of actions within the planner, such as moving from one place to another, turn light on and off, open and close doors, and push and move objects. As per SRI, SHAKEY considered the first integration between AI and robotic technology (Nilsson, 1984).

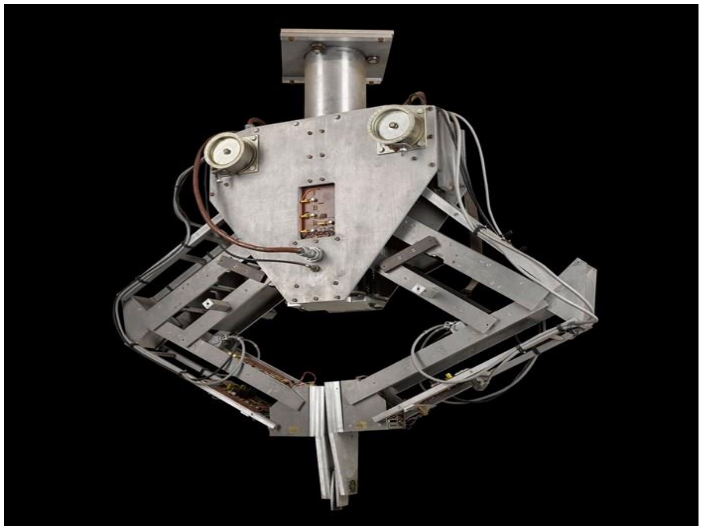
Figure 3.5 SHAKEY the Robot



Source: (Nilsson, 1984, p.2)

At the Machine Intelligence and Perception department at Edinburg University, the experimental robot FREDDY (Figure 3.6) was built between 1969 and 1971. It was consisting of a rotating platform that produced three degrees of freedom with two wheels, cameras, and sensors connected to a computer. FREDDY can be moved by commands from the computer, then the camera will capture the objects and recognize them. The programing language was the first functional programming language (POP-2). And Elliot 4130 computer with 64k 24-bit word was used. And later on, it was upgraded into 128k. Also, Honeywell H316 minicomputer used to control the camera and motors. Indeed, the purpose of developing this robot was to identify and locate objectives. However, FREDDY II was introduced in the period between 1973 and 1976 with 5 degrees freedom and a big hand, which can be moved up and down. The hand can rotate around vertical access and rotate objects in a gripper and around horizontal access. The robot can locate a heap of parts and arrange it into a complete assembly. It locates the heap by the side camera, inspects the part by the head camera, picks up the part and put it down at the correct place and at the correct orientation, and it will complain if there are any missing parts (Ambler, Barrow, Brown, Burstall, & Popplestone, 1973).

Figure 3.6 FREDDY the Robot

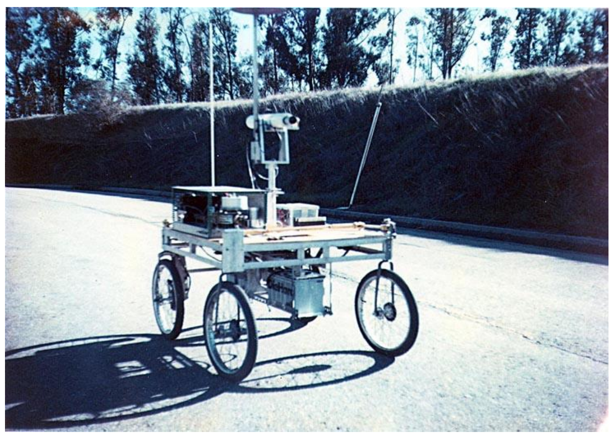


Source: (Ambler et al., 1973, p.304)

In 1979, SRI produced the Sanford cart (Figure 3.7), which was a remotely controlled mobile robot with a TV camera (Moravec, 1979). The cart was driven by a computer program. It can generate knowledge from the environment around it, using 3D images captured by the TV camera system. Accordingly, it can detect the objects around it and avoid them while moving, up to reach its programmed destination. However, it was slow, because its speed was one meter per ten minutes. And for each one meter, it stops and starts taking pictures, process them and then move to another one meter, and so on. Therefore, it may take five hours to run thirty meters. To run the car, a camera calibration should be done as a first step, by parking the cart in front of a wall with drawn spots. Then the cart should be driven manually to its obstacle path, and an obstacle avoiding program will start running by asking for cart destination with respect to heading and current position. After getting the required answers, it will start the maneuvers process (Moravec, 1983).

1980 was the real breakthrough year for the expert systems and it got wider spread. The idea of these systems was to imitate human expert decision-making ability (Tan, 2017). However, the first expert system General Problem-Solving (GPS) program, was introduced by Newell, Shaw, and Simon (1959). It was designed to works on problems that can be represented as objects and operators. The operator is a set of processes that can be applied to a certain object to produce a new object. And objects are the input of the system. For instance, in the Chess game, the chess positions represent the objects, the movements represent the operators and the new positions represent the output (i.e. the new object). Figure 3.8 shows the executive organization of GPS. Another expert system was introduced by Lederberg (1963), "DENDRAL", and it was available in the market in 1965. It is a computer software based on heuristic analysis and was using the rule of thumb to produce some possible chemical structures from the use of experimental data and mass spectra with a chemistry knowledge base. Petrick (1971) developed the Macsyma, which represents the oldest computer algebra system for general purpose. And it became a commercial product in 1982 and it has been used widely up to date.

Figure 3.7 Stanford Cart



Source: (Moravec, 1983, p.2)

Figure 3.8 Executive Organization of GPS

Source: (Newell et al., 1959, p.7)

The Deep Blue supercomputer from IBM was the first world chess champion computer, when it defeated the world champion Garry Kasparov in 1997 (Hsu, 1999). The system is consisting of 30-node IBMRS/6000 SP computer, each node contains 120 MHz microprocessor, 480 single-chip search engines, and 16 chess chips per processor. Each node has 4 GB Hard disk and 1 GB RAM. The chess chips can search up to 2.5 million positions per second and each chip communicates with its node by microchannel bus (Campbell, Hoane, & Hsu, 2002).

In 2005, Stanley, an autonomous vehicle developed by researchers at Stanford University and Volkswagen. It won the DARPA grand challenge (Figure 3.9a). The vehicle root was attached with a set of sensors, and the steering was attached with a DC motor to enable electronic driving control with actuator attached to the shifter to shift the vehicle between parking, reverse and drive gear positions. Global Positioning System (GPS) and 5 laser sensors were attached to the vehicle roof and positioned with different angles to measure the close area in front of the vehicle and up to 25 meters. Also, a camera was attached to the vehicle roof for long area perception in front of the vehicle. Another 24 GHz radar sensors were attached to the roof to cover 200 meters distance. The speed and steering angle data are sensed automatically and sent to a computer system (Figure 3.9b). The computer with a Linux operating system was installed in the vehicle trunk (Strohband et al., 2006).

Figure 3.9 Stanley Autonomous Vehicle

(a) *(b)*

Source: (Strohband et al., 2006, pp.663-664)

The term big data were emerged recently to represent a collection of data that can't be processed by traditional computer programs. The big data characterized by three items: volume, velocity, and variety. The volume is related to a huge amount of data, velocity refers to a rapid increase of structured and unstructured data, and variety is about using a different type of data to analyze a single issue or situation (Zikopoulos, Eaton, DeRoos, Deutsch, & Lapis, 2011). The AI-based systems are introduced as a tool that can deal with this type of data. By using computer-based approaches for the recognition and learning of difficult patterns, the AI can deal with the big data volume. Also, by using high-speed computer-based decisions to deal with the velocity. And finally, the variety is relieved by using AI to capture, structure, and understand unstructured data (O'Leary, 2013).

3.2.2 Machine Learning (ML)

As a part of AI, ML is related to giving computers the ability to learn by using statistical techniques. ML was coined by Samuel (1959). He mentioned two approaches related to ML problems. The neural-net was the first approach and it was related to stimulating a learning behavior inside a switch connected randomly. The second approach was about making a quite organized network, which is designed to learn specific things. He considered the second approach as more efficient than the first one. ML can be categorized into the following research focus (Carbonell, Michalski, & Mitchel, 1993):

1. **Task-oriented research area:** improving the performance in a predetermined set of tasks, by developing and analyzing learning systems.
2. **Cognitive stimulation:** computer simulation and investigation in human learning approaches.
3. **Theoretical development:** investigation and analysis in learning methods and algorithms.

In robotic technology, the knowledge that the robot has to learn can be categorized into the following knowledge types (Mahadevan, 1996):

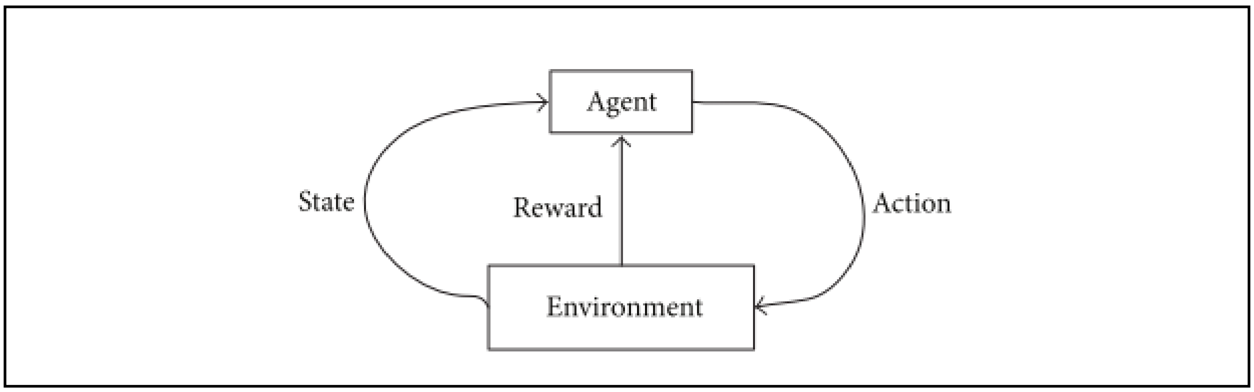
1. **Control knowledge:** it is related to providing the robot with a control program, which can be used by the robot to perform a set of actions to achieve specific goals.
2. **Environmental model:** which is about the ability of the robot to update its knowledge, to be able to adapt to the unstructured new environments.

3. **Sensor-effector models:** the sensor part is to give the robot some of the human capabilities, like sensing, hearing, touching, moving, and using algorithms that need environmental feedback. The effector part is about the ability of robots to interact with the environment, and it is usually attached to the end of the robots' arm.

In fact, the term Robot Learning is a result of the interaction between ML and robot technology. It is related to:

1. **Reinforcement learning:** it is a model of ML, which is appropriate to be used with robots. It is presuming the world as a set of environments and agents (i.e. robots) states S, the agent can execute a set of actions A, roles to explain what the agent observes, and the time which is represented by discrete steps. The agent will be given a reward for each performed action (Smart & Kaelbling, 2002), as shown in Figure 3.10.

Figure 3.10 Reinforcement Learning Framework



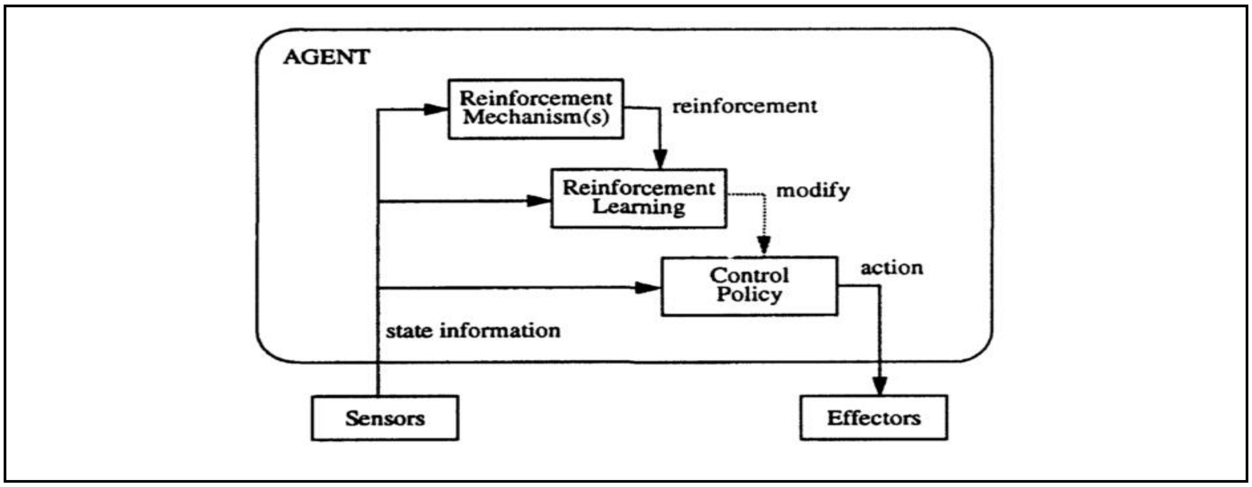
Source: (Zhou, Zhu, Liu, Fu, & Huang, 2014, p.3)

The agent (Figure 3.11) has the following components (Lin, 1993):

a) **Sensors:** to gather information about the state of the surrounded environment.
b) **Effectors:** to enable the agent to change its environment.
c) **Reinforcement mechanism:** to produce a signal after each executed action.
d) **Reinforcement learning:** it is related to the feedback information from the environment.
e) **Control policy:** it is related to situation-action planning.

The reinforcement learning agent is reactive, which means it can transform the collected experience into situation-action rules (Control Policy), and adaptive that uses feedback information to enhance its performance. Also, when compared to other learning systems, it is less dependent on trainers because it is learning from reinforcement mechanism, and less dependent on the previous field of knowledge since it's an inductive learner. Moreover, the reinforcement learning has different types of algorithms for a different use, such as Q-learning, Deep Q Network (DQN), Asynchronous Actor-Critic Algorithm (A3C), and Deep Deterministic Policy Gradient (DPG). For instance, DQM, which applied in the Atari 2600 video games, combines reinforcement learning with artificial neural networks (Zhan, Ammar, & Taylor, 2016).

Figure 3.11 Reinforcement Learning Paradigm

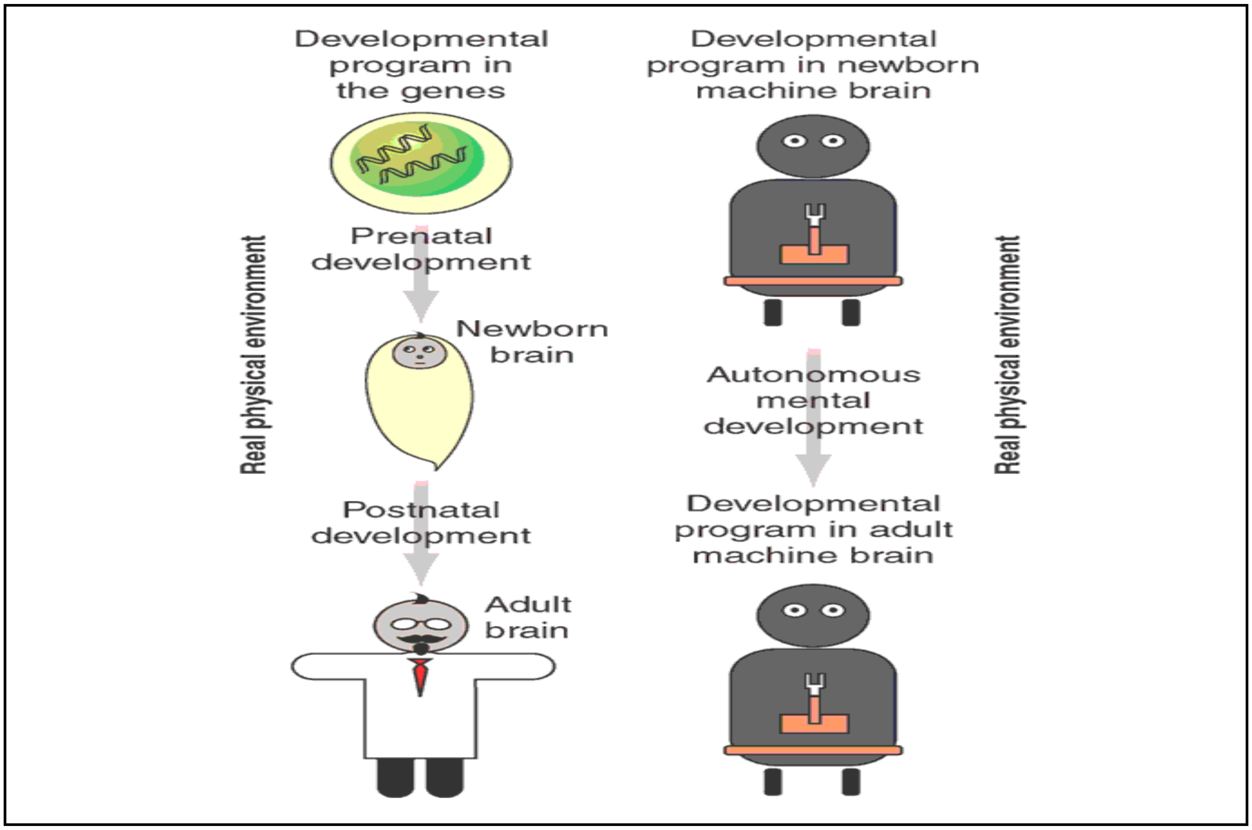


Source: (Lin, 1993, p.3)

2. **Developmental robotics:** it concerns in studying the development of lifelong cognitive behaviors and it focuses on robot Autonomous Mental Development (AMD), such as artificial emotions, self-organization, and self-motivation (Xu, Min, & Xiao, 2014). AMD is related to the use of robot sensors and effectors to develop the mental capabilities (Figure 3.12) by the autonomous interaction with its environment (Weng et al., 2001).
3. **Evolutionary robotics (ER):** is the application of an artificial peer of natural Darwinian evolution to develop robots artificial brains, sensors, and bodies (Arvey, Paolo, Wood, Quinn, & Tuci, 2005). It based on evolutionary computation by repeating cycles of controller convenience and selection, which are almost similar to the natural evolution of generations. For each cycle, each controller from a population of candidate controllers is set to perform a specific task, and to be involved after that in an evaluation period. The evaluation is based on a fitness function, which is a function used to measure if the design

is fulfilling its targets, and modification is repeatedly performed based on the fitness function evaluation. Then a Genetic Algorithm (GA) is applied based on the information resulted from fitness function to select and replicate the fittest candidates to next-generation (Nelson & Grant, 2006).

Figure 3.12 Mental Development



Source: (Weng et al., 2001, p.599)

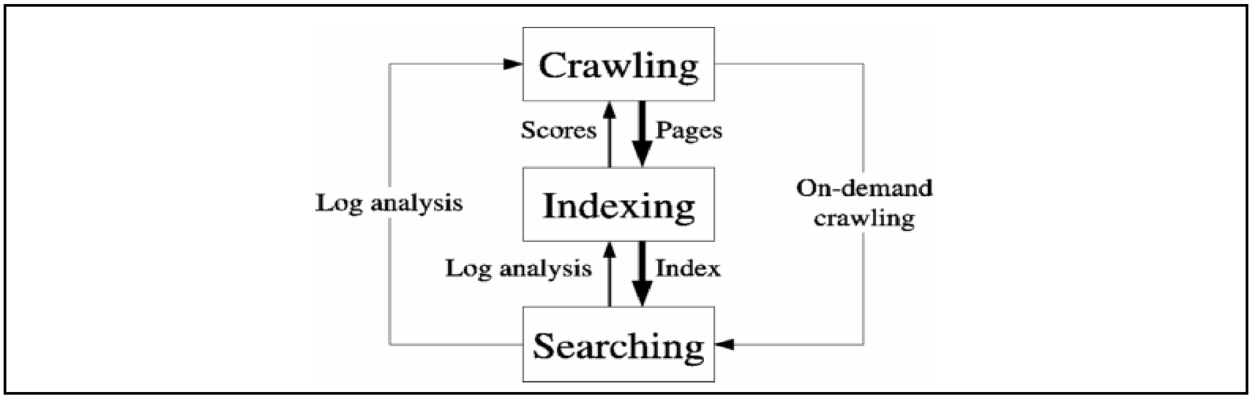
3.2.3 Bot

Bot (i.e. software robot) is an intelligent software robot that can perform automated tasks over the internet, such as Crawler bot, or as an application installed into a computer, such as offline chatbot (Etzioni & Weld, 1995). Here are some examples of bots:

1. **Crawler bot (or Spider)**: this is a system that can download a bulk number of webpages. It is used as the main component of search engines by indexing webpages and gives users the ability to request queries inside this index and locate the web that matches these queries. Also, it is used for archiving webpages for future use, for data mining (i.e. large data is analyzed to find a pattern) and for monitoring web service to send notifications to

clients about webpages that match their queries (Olston & Najork, 2010). Figure 3.13 shows an example of the Crawler engine architecture.

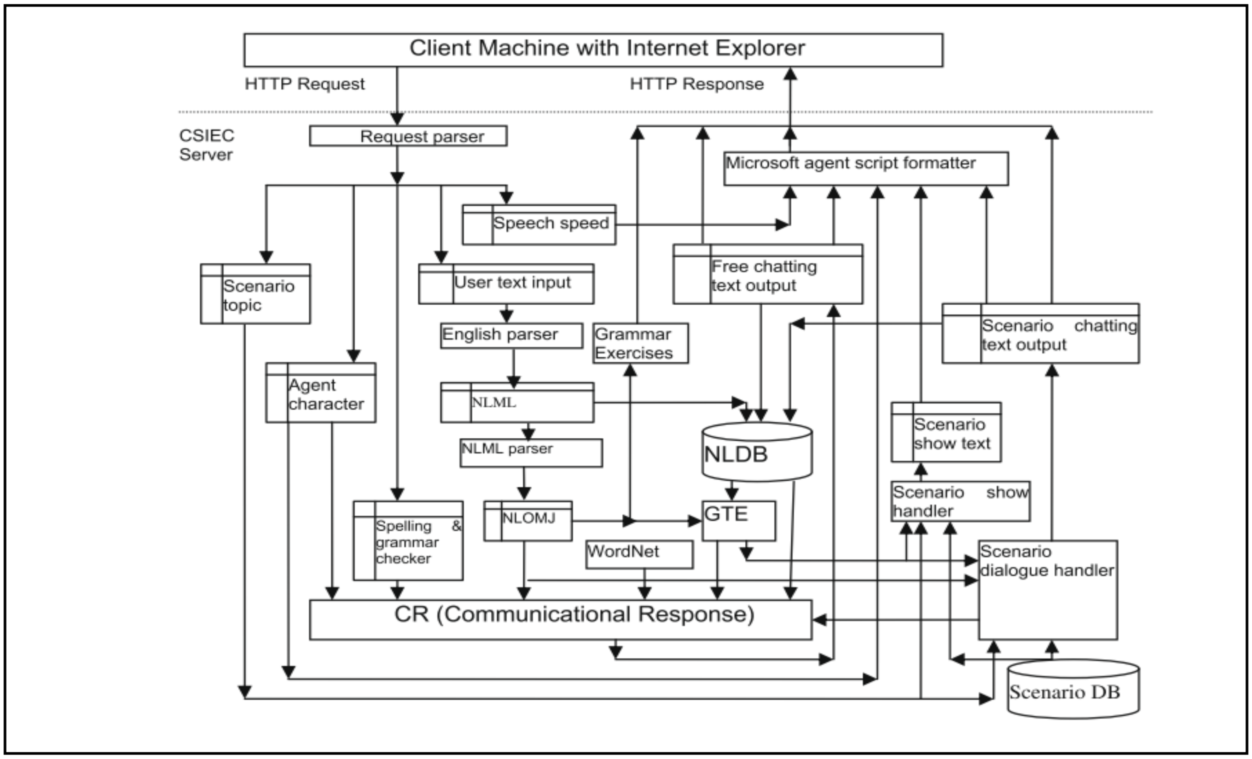
Figure 3.13 Search Engine Architecture



Source: (Castillo, 2005, p.5)

2. **Chatbot**: which is an AI program that used to simulate human behavior through audio or textual conversation (Shawar & Atwell, 2007). It could be used for language learning like Computer-Assisted English learning chatbot (CSIEC), which its architecture is shown in Figure 3.14 (Jia, 2009). Or for psychotherapy use as DOCTOR chatbot (Weizenbaum, 1976).

Figure 3.14 CSIEC Architecture



Source: (Jia, 2009, p.251)

3. **Social bot:** it is a type of bots used in social media applications. They are acting like humans and they can affect public opinion toward any direction by their interaction with humans through Facebook posts, Twitter tweets, automatic instant messages, and so on (Abokhodair et al., 2015). Some of these bot accounts could be used for entertainment, support, and help or it could be harmful (Davis, Varol, Ferrara, Flammini, & Menczer, 2016). The massive spread of fake news over social media is considered a global risk that may affect all aspects of social, political, and economic life. Unfortunately, the fingered are pointed in some cases into the bad social bots (Shao et al., 2017). Their behavior becomes more similar to humans, especially with the development of AI and ML (Adams, 2017).

Recently, Babylon health, which is a digital healthcare company in the UK, launched an application that works as a digital doctor. The application is based on a combination of AI technologies, including language processing for patients' symptoms description, expert systems to operate the large databases, and ML to match between symptoms and conditions. The app work like a chatbot. It starts the conversation with the patients by asking them a couple of questions to be able to diagnose their symptoms. If the app finds some doubt about the decision, it transfers the patients' call to a human operator. The app has the ability to decide if the condition needs urgent treatment or it needs a rest with a simple drug. The statistics showed that 40,000 users used the application. 40% of them were asked to do self-treatment and 21% were directed to emergency care from both AI and human operators. Indeed, this app isn't going to replace the human physician, but at least it can minimize the load by handle conditions that can be treated online. In the UK, it is integrated with the National Health Service (NHS). And the service also is available in Rwanda, in its setting up process in Canada, and expected to be launched soon in the USA, Middle East, and China. The adoption and diffusion of AI applications through formal institutions are a good sign of the effectiveness of these technologies, which gives another evidence of the possibility to see AI in human life and as it has been imagined in science fiction novels (Heaven, 2018).

3.3 Literature Review of Robot Technologies

This research is interested in using robots in the service context. It is important to point to service robots as an autonomous and adaptable device that can communicate, deliver service, and interact with consumers (Wirtz et al., 2018). And as the interaction with humans is a part of these robot tasks, these robots should have social skills to succeed in delivering the intended services (Share & Pender, 2018). In fact, there are many previous studies regarding the formulation of human-like interaction of the service robots. However, the actual response of consumers toward the service robots is still under investigation and little attention has been paid to this context (Stock & Merkle, 2018). This will be the focus of this research while studying the literature review, to be able to formulate a model that can explain the acceptance of such robots.

In general, three types of factors can influence behavior decision: the positive or negative results associated with performing the behavior, agree or disagree of an influential person or group on performing the behavior, and the factors that may simplify or hinder the behavior execution. In the robot technology context, the first factor is related to the individual evaluation of using robots, the second one is related to social influence, and the third factor is related to the contextual aspects, which are important while using robots (Graaf & Allouch, 2013). Meanwhile, the modern researches in human-robot interaction proposed that human treats the robot as a social entity with specific social roles and characteristics. In other words, human sees the robot as a human being, especially when there is a direct interaction between them. Therefore, the design of robots should be social in its structure, to be able to get involved in the human owned environment (Young, 2010). For instance, in autonomous wheelchair robots, people are positively perceiving the ability of robots to call them by their names. This could be considered as an important aspect of human-robot interaction success and robot acceptance (Kanda, Shiomi, Miyashita, Ishiguro, & Hagita, 2010).

Extensively, robots can be used to perform service tasks (utilitarian) and they can build a long-term relationship through their interaction with human-being (hedonic). For example, service robots could be considered utilitarian systems, as they are designed to perform a functional task, such as in healthcare, education, and frontline services. On the other hand, they are considered as hedonic systems too, because they need to make a good and long-term relationship with humans in their environment (Klamer & Allouch, 2010). In the same context, Uncanny Valley, which was introduced by Mori (1970), illustrated the differences between industrial robots (mostly utilitarian) and humanoid robots (utilitarian and hedonic nature). The author proposed a relationship between the degree at which an object looks like a human and the human emotional response to that object. He pointed to the functionality of the industrial robots, which is the most important aspect for the designers and it should match or exceed workers' functionality. However, industrial robots don't look like humans in terms of the appearance. The author mentioned the possibility of making the robot with legs, arms, and face to look like a human, which in turn could increase the familiarity sense of humanity toward robots. Another important aspect proposed by Mori (1970) was the motion effect. He considered the motion as a sign of life. Furthermore, when motion is programmed in such a way to look like human motion, the sense of familiarity could increase too. On the other side, matching robot appearance realism and behavior realism can enhance human-robot interaction. Where realism could be defined as the degree at which humans believe that robots appear and behave realistically. But the author pointed to the degree at which the robot is getting more realism, it might be perceived as unpleasant by the human. In other words, at some level, the realism will improve human-robot interaction and impact positively the acceptance of robots. On the contrary, it will negatively affect the acceptance if it goes beyond normality (Bartneck, Kulić, Croft, & Zoghbi, 2009; Graaf & Allouch, 2013). Regarding robot appearance, some researches classified robot based on its appearance as followed (Moro, 2018):

1. **Human-like robot**: the appearance of robots looks like a human being (e.g. two legs, two hands, head, and face).
2. **Animal-like robot**: here, robots take an animal look with four legs, tail, etc.
3. **Machine-like**: no human or animal features are included in the appearance design of robots, such as in industrial robots.
4. **Character-like**: the robot may be designed to look like a celebrity cartoon character.

It is important to note that in the human-robot interaction context, the attractiveness and human-like appearance are being used to evaluate the robots, in order to be accepted or rejected (Destephe et al., 2015).

The utilitarian aspects of robot technologies are related to the functionality and the required tasks from using such technologies. These aspects have been studied well in literature by implementing the technology acceptance models in investigating the acceptance of robotic technology, such as Technology Acceptance Model (TAM) for Davis (1985) and Unified Theory of Acceptance and Use of Technology (UTAUT) for Venkatesh et al. (2003) and their extensions. The TAM constructs perceived usefulness, which is defined as user perception of activities (e.g. work, home, and social tasks) enhancement by using robots, and the perceived ease of use, which is related to the simplicity and the free efforts that are associated with the use of robots. Both constructs are roughly corresponding to UTAUT constructs: performance expectancy and effort expectancy, respectively. Another important utilitarian factor is the adaptability, which is related to the user perception of the robot's ability to adapt to the changes in human needs (Heerink, Kröse, Evers, & Wielinga, 2010b). These three factors showed a significant impact on human-robot interaction (Graaf & Allouch, 2013).

For the hedonic side of robotic technology, the literature pointed to enjoyment and attractiveness as major variables in the acceptance of this technology. Enjoyment itself can be defined as the pleasure associated with the use of the robot (Heerink et al., 2010b). Indeed, feeling enjoyed when using robots will be reflected positively on the acceptance of it (Shin & Choo, 2011). The enjoyable human-robot interaction is related to make humans more familiar with this type of interaction. This enjoyable interaction can be achieved through the utilization of human propensity to interact with social entities or to provide robots with the ability to express their emotions by, for instance, vocal communications (Romportl, 2015). Moreover, the attractiveness is related to the physical appearance of robots (Lee & Nass, 2003).

Another important aspect of robots is social presence. Which can be defined from the human-being point of view as to how human simulate mentally others intelligence (Biocca, 1997). And in terms of how humans see robots, it could be defined as the psychological state in which humans see the robot as an actual social actor, instead of seeing it as an unhuman social actor (Lee, 2004). Certainly, social presence acts as an important role player in human-robot interaction (Lee, Park, & Song, 2005). Gresham and Elliott (1990) introduced the Social Skills Rating System (SSRS), to be able to evaluate human social behavior. The scale is consisting of cooperation, assertion, responsibility, empathy, and self-control. This scale was applied to the human-robot interaction field and introduced the following social abilities aspects: cooperation, assertion, responsibility, show competence, express empathy, gain trust and exhibit self-control (Heerink, Kröse, Evers, & Wielinga, 2009b). However, the sociability of the robot itself is something perceived and shaped by the human mind, as the robot is still a machine programmed to be perceived in terms of its behavior (Graaf, Allouch, & Dijk, 2016). Also, Individuals are going to perceive the social robot as a new entity that can work with them in their private space and can explicate and interact intelligently with its environment (Young, Hawkins, Sharlin, & Igarashi, 2009). Additionally, robot sociability is playing an important role in stimulating the interaction between robots and humans to establish the acceptance of these robots (McColl, Louie, & Nejat, 2013) and in building a long-term relationship among humans and robots (Heerink et al., 2010b).

In social settings, the ability to provide a social companionship can support human-robot interaction (Lee, Jung, Kim, & Kim, 2006). For instance, in applications where robots are used for elderly healthcare, robots need to be a social companion. This ability could be seen as an important stimulator of the adoption and the diffusion of these robots (Klamer, Allouch, & Heylen, 2011). Actually, some studies in the literature consider the robot companion as a separate research line and investigated the factors that could impact human acceptance of robot companion (Dautenhahn et al., 2005). Indeed, some robots are designed only to provide a pet-like companion to improve human health and the psychological state of patients and elderly people (Broekens, Heerink, & Rosendal, 2009).

The term "Anthropomorphism" is used to represent the human tendency to refer human-being characteristics into the robots to rationalize their behavior (Duffy, 2003). Human-being characteristics, for instance, include human-like body, human face, speech ability, and eye movement. These characteristics can be used to achieve a meaningful human-robot social interaction (Lee et al., 2005). The robots should look like humans in terms of functionality and structure if the purpose of using robots is to interact with humans. Nevertheless, if robots are going to learn from humans, then they have to behave like a human (Billard, 2003). Therefore, anthropomorphism can act as a technique in which social interaction can be simplified. Thus, the best way to use anthropomorphism is by making a balance between human imaginations about the robot's abilities and the actual functionality of the robots that are required to support the human-robot interaction process (DiSalvo, Gemperle, Forlizzi, & Kiesler, 2002). Also, human-like appearance could stimulate the social presence and enhance human-robot interaction when compared to the functional robots (Kwak, 2014). On the other hand, some researches in the literature mentioned the term "Animacy", to represent the robot like-life or the perception of life. It showed an impact on human-robot interaction, besides its impact on the acceptance of using the robots (Koda, Nishimura, & Nishijima, 2016). But, other authors pointed to the overlap between anthropomorphism and animacy, and the could be considered as one combined and extended concept (Bartneck et al., 2009; Kim & Shin, 2015). Furthermore, anthropomorphism could be used to judge the animacy and likeability of robots, as shown in some of the previous experiments (Castro-González, Admoni, & Scassellati, 2016).

Knowing individuals' emotions, perceptions, and anticipations about the existed social interactive technologies in their environment is a very important aspect in the designing process and the acceptance of social robots. Indeed, designing robots that can capture the user's intention in the long-term is a challenge for robots' designers. They have to focus on the enjoyability, usability, and sociability of robots (Graaf, Allouch, & Dijk, 2017). Actually, human emotional arousal and pleasure during the interaction with social robots could impact the intention and use behavior significantly, positively or negatively, and upon the human emotional state (Damholdt et al., 2015). Hence, perceived arousal and pleasure encourage behavioral engagement, such as in autism therapy using social robots (Rudovic, Lee, Mascarell, Schuller, & Picard, 2017). In general, arousal and pleasure could be consistent for different types and configurations of robots (Zhang et al., 2010). For instance, the effectiveness of the interaction between robots and patients may be affected positively by the positive arousal and pleasure emotions. The perception of these emotions could be related to robot features, especially the affective ones, and from the patients' perspective (Zhang et al., 2010, 2009). As well, the interaction between consumers and robotic staff in hospitality services requires some degree of arousal and pleasure emotions. These emotions represent a core principle in the interaction between consumers and hospitality staff (Lu, Cai, & Gursoy, 2019). Likewise, in collaboration tasks between humans and robots, the perceived arousal and pleasure of humans toward robots could enhance the performance outcomes, such as in serious games collaboration between humans and autonomous robots (Jerčić, Wen, Hagelbäck, & Sundstedt, 2018).

The trust dimension is showing itself as a vital player in the human-robot interaction context. It represents a psychological state of trustor about the willingness and ability of the trustee to help and cooperate in attaining trustor goals (Simpson, 2007). Certainly, human represents the trustor, robot represents the trustee, and tasks represent the goals (Brule, Dotsch, Bijlstra, Wigboldus, & Haselager, 2014). It is a strong predictor of human-robot interaction success, which could impact positively the acceptance and the diffusion of robot technology (Rau, Li, & Li, 2009).

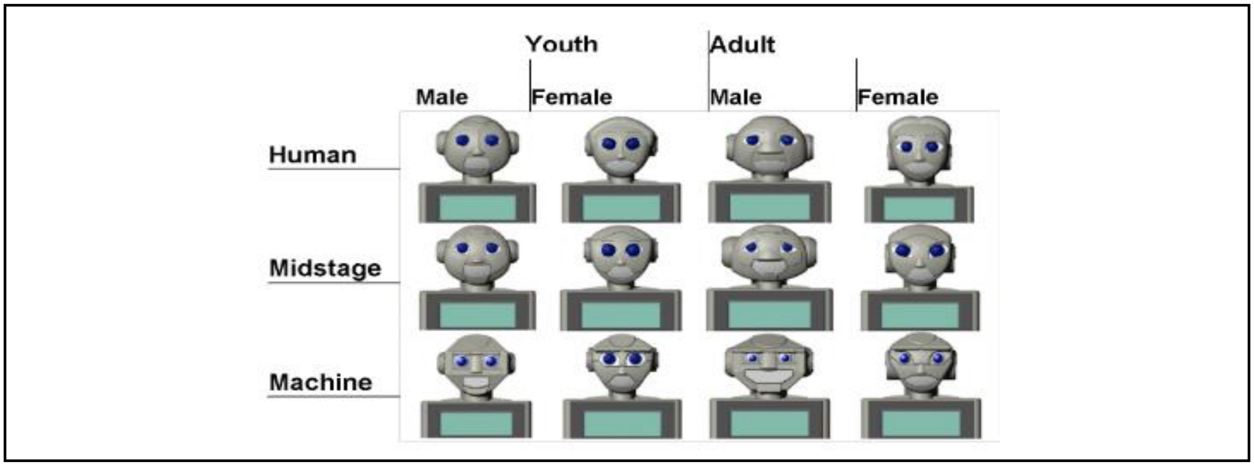
During the interaction with the robot, human safety is a key component of the human-robot interaction process. Different studies in literature dealt with safety construct in both industrial and service robots acceptance (Bartneck et al., 2009). In general, the perceived safety while interacting with the robot is somehow connected to anxiety. When humans feel safe, they could control and reduce the feeling of anxiety (Chung & Shin, 2015). Additionally, the importance of perceived safety depends on robot applications. For instance, if there is no direct contact between humans and robots, safety could not be an issue. On the contrary, in healthcare, and education, the perceived safety could impact the robot's acceptance significantly (Destephe et al., 2015).

It should be mentioned that there are conflicts that could be resulted once humans apply some kind of norms and stereotypes on the robots, which may cause a challenge in human-robot interaction. These norms and stereotypes may explain why a specific behavior of the robot will be accepted or rejected (Graaf & Malle, 2018).

3.4 Studies about Robot Technologies

Goetz, Kiesler, and Powers (2003) proposed that matching robot appearance and tasks will increase its acceptance. They tested this proposition by implementing three experimental studies. In the first experiment, they developed 12-2D robotic heads with three human-likeness levels: human, human-machine, and machine looks. Also, they made a mix between youth, adult, male and female looks (Figure 3.15).

Figure 3.15 Robots in Survey

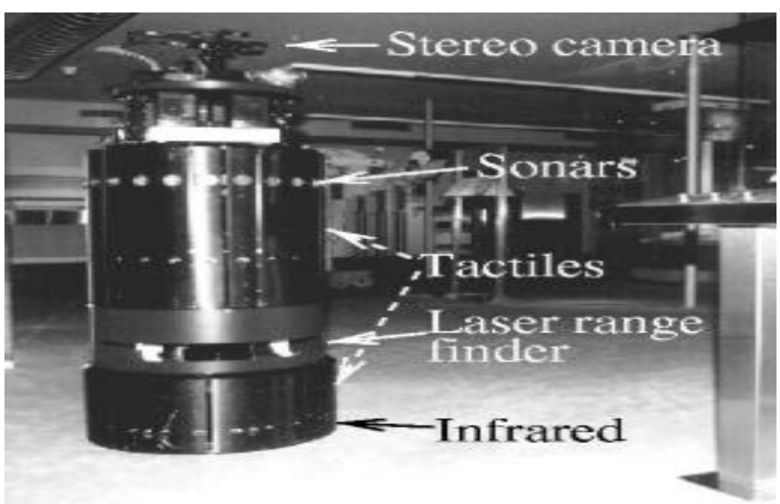


Source: (Goetz et al., 2003, p.56)

Most of the participants preferred human-like shapes instead of machine ones, especially in social job types (e.g. in hospitals, museum tour-guides, and food delivery). However, participants showed more interest in machine-like shapes for traditional and realistic jobs (e.g. customs inspectors and security guards). These results confirmed the importance of the robot's appearance to be compatible with the job type in which robots will be employed. For instance, human-like appearance is a major predictor of robot acceptance in social interaction settings. In the second experiment, the authors tested the difference between serious and playful robots in terms of human commitment to robots' directions. The robot in both scenarios asked participants to perform some exercises seriously for the first phase, and playfully for the second phase. The participants rated the serious robot higher scores than the playful one. And finally, the authors in their third experiment showed that participants were more committed to the playful robot than the serious one in enjoyable tasks. These experiments confirmed the relation between robot appearance and human perception of it. Furthermore, the social cues of the robot should be compatible with its expected tasks to be accepted by humans.

So far, human perception of robots varies as the application itself is varied, and the importance of the robot's characteristics is dependent on its applications too. For example, an interactive robot called RHINO (Figure 3.16) was used as a museum tour-guide in Germany in 1997 by Burgard et al. (1999), to examine how it will interact with people in public places and how people will perceive it.

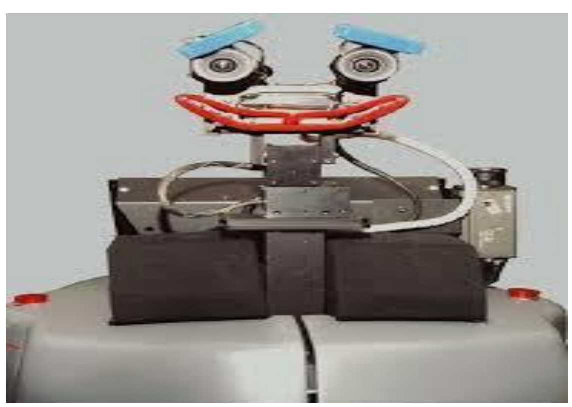
Figure 3.16 RHINO



Source: (Burgard et al., 1999, p.4)

The importance of this experiment was the transfer of robot use from closed offices to the public environment, where more obstacles, constraints, and crowds surrounding and affecting robot tasks. Therefore, the challenge was to implement a robot that can cope with surrounding environment obstacles, to design an interface that perceived ease for the users, and to include social features that attract the users in terms of human-robot interaction context. Besides the technological aspects of the robot in terms of software and hardware features (e.g. user interface, task planner, map builder, localization, path planner, collision avoidance, motors, and sensors), the authors gave important attention to the human-robot interaction side. They pointed to the ease of use and enjoyableness as the main two important criteria that should be embedded within the robot design. Two types of interfaces were associated with the RHINO: on board and web interface. In the onboard interface, the robot gives the ability to the users to choose a tour and listen to an introduction about the museum and its exhibits. The robot then starts moving while playing a piece of music to add some entertainment to the tour. The direction of the camera is pointed to the direction of the robot motion. For each exhibit, the robot gives a brief explanation about the exhibit by voice, and then leave the choice to the user to continue in listening or to move to another exhibit. On the other side, the web interface gives users four capabilities: control, monitoring, background information, and discussion forum. Moreover, the robot's ability to react with people by welcoming their presence through its horn sounds and its ability to slow down its speed to ask people to clear the way to pass were considered the most enjoyable sides of RHINO. Two years later, a new generation of RHINO had developed: Minerva (Figure 3.17), and it was tested in the Smithsonian museum in the USA in 1999. More people and wider areas had challenged the Minerva.

Figure 3.17 Minerva



Source: (Thrun et al., 1999, p.2000)

Unlike RHINO, Minerva uses its camera images for localization, its motion planner uses information acquisition during paths planning, and it can learn maps from scratch. Also, it has a face, which helped it to attract people and express the emotional states (Thrun et al., 1999). In fact, the benefits that could be driven from these two experiments are related to the differences in the degree of attractiveness and acceptance of those robots when a human-like face is included in the design, besides the ability of robots to express their emotions. The authors mentioned the value of these changes in the later robot, and how it affected positively the human perception and interaction with robots.

Despite that there is a difference in the interaction degree among humans and robots, the interaction still exists for most robots applications, since the robots have been designed to work with humans or to perform work for them. Goodrich (2008) discussed the key problems associated with the human-robot interaction in his survey. He defined five attributes that can influence the interaction process:

1. **Autonomy** behavior and its degree: it is about the degree at which the robot can perform its tasks without any support from humans, which could be considered critical to the success of the interaction process. Furthermore, in the human-interaction context, the level of autonomy is dependent on the level of interaction and the required level of autonomy from both sides. Sheridan and Verplank (1978) classified the level of control in their report about the undersea teleoperators control into:
    a) Full human control.
    b) The computer acts autonomously.
    c) The computer offers a set of alternatives.
    d) The computer minimizes the choices.
    e) The computer advises for a single choice.
    f) The computer executes that choice upon human approval.
    g) The computer offers to human countdown to approve that choice before the automatic execution.
    h) The computer executes that choice automatically and notifies the human.
    i) The computer notification upon human request.
    j) The computer notified human upon its decision.

2. **Exchange** of information: it is related to the communication ways between robot and human, which could be formatted through speech, visual, gestures, physical interaction, or audio (non-speech). This communication format is depending on the nature of robot use. For instance, speech ability could essentially not complementary in companion robots for healthcare use (Kim, You, Kim, Hahn, & Yun, 2017). Furthermore, the visual interface also could be necessary for urban search and rescue applications (Baker, Casey, Keyes, & Yanco, 2004).
3. **Teamwork:** it is concerned about how many people have to work with or control the robot, and the required number of robots to perform a specific task. The number of robots that one person can control is depending on the task, robot autonomy, and the communication format.
4. **Training, Learning, and adaptation:** training users to be able to interact with robots, and how the training is classified in terms of simplicity or specialized training are dependent on the robot use. For example, in companion robots, general and simple instructions can give the user an overview of how to deal with robots. However, in surgical robots, specialized training should be undertaken to use these robots (Beasley, 2012). Also, robot learning and adaptability could be considered important and useful in behavior design and task-specific learning robots. Moreover, robot adaptability could be significant for long-term interaction and the acceptance of robots (Graaf et al., 2016).
5. **Tasks shaping:** it is related to how tasks should be done with the new technology when compared to how it is done without it.

Goodrich (2008) tried also to develop a unified theme for human-robot interaction problems. He suggested the following themes:

I. **Interactive learning**: humans and robots work together to improve gradually understanding ability, autonomy, and interaction.

II. **Team organizations and dynamics**: to enable the multiple interactions between multiple humans and robots, it is important to form team interactions and dynamics through setting up support tools, communication protocols, and organizational structure.

III. **Dynamic autonomy, mixed-initiative interaction, and dialog**: it is fundamental to make the interactions and behaviors flexible, to be able to cope with the complexity of the environment.

IV. **Telepresence and information fusion in remote interaction**: it is about the remote interaction between humans and robots, which is related to the advancement and innovation in communication technologies to reduce problems associated with this interaction, such as delay and bandwidth limitations.

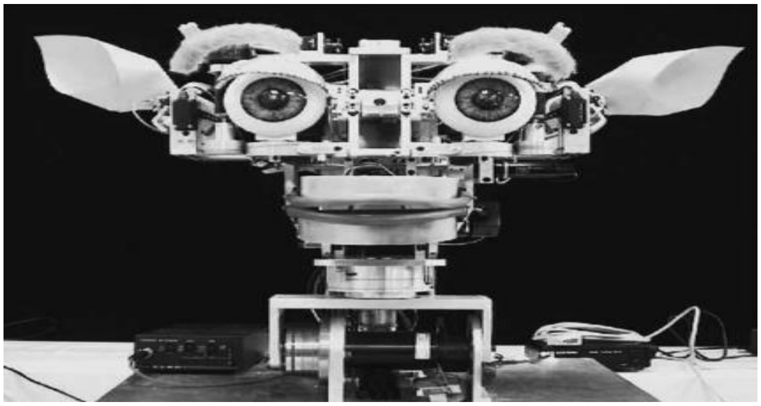
V. **Cognitive modeling**: by developing a cognitive model for human behavior and reasoning to make the robot behaves based on this model. And to allow the robot to adjust the exchange of information based on the human cognitive state.

The functionally part of the robots needs to reinforce their ability to interact with humans in anthropomorphic, engaging, or entertaining ways. These abilities are embedded in the success of a robot's commercial applications. Breazeal (2003) studied social robots and pointed to four classes of them:

1. **Socially evocative**: it is about the anthropomorphic of robot's technology, with a view of interacting with these technologies.
2. **Social interface**: in this class, the robot uses the communication methods and human-like social cues to encourage interaction with humans.
3. **Socially receptive**: humans in this class formulate the robot's behavior, and robots are more perceptive to human social cues.
4. **Sociable**: robots in this class perceive humans' social cues and modeling them socially and cognitively to be able to interact with them.

The author focused on the latter class (sociable) by implementing a case study using the Kismet robot (Figure 3.18). The design purpose of this robot was to be able to interact socially, physically, and effectively with the humans, and to learn from them. The Kismet skills supported the ability to cope with environment complexity, to perceive human cues, and to make humans able to perceive this robot. These skills include: find shared preferences by the ability to direct the robot attention (Scassellati, 2002), the ability to produce meaningful and readable feedback to the human (Breazeal, 2003a), the ability to understand the human feedback (Breazeal & Aryananda, 2002), structuring learning episodes by its ability to take the turns (Breazeal, 2002) and the ability to adjust the interaction to generate an appropriate learning environment (Breazeal, 2003a). The evaluation of the interaction between the humans and Kismet was established based on the following questions: did Kismet perceived and responded to the human cues? did humans perceived and responded to Kismet cues? did they adapt to each other? Actually, the study pointed to the importance of robot design in terms of robot ability to express feedback, perceived social cues, and regulate the exchange with people in such a way that is appropriate for learning.

Figure 3.18 Kismet



Source: (Breazeal, 2003b, p.170)

Sparky was used to reform new ideas about interactive robots. It had an expressive face, moving head on a long neck, and moving wheels (Figure 3.19). A human operator was using a game controller to send robot commands. The operator specified the movement direction and facial states, and the onboard processor translated the operator commands and drove the motor upon these commands. As a result of their study, Scheeff et al. (2002) affirmed the importance of robot emotional states in getting the human attention. They recommended to choose reasonable states and translate it into a body language. They called it body-centric techniques, which need further investigations in future.

Figure 3.19 Sparky

Source: (Scheeff et al., 2002, p.174)

An interesting experiment was performed to compare the consumer's perception of Frontline Service Robots (FSR) and Front-Line Employees (FLE) during the service encounter by Stock and Merkle (2018). The participants in this study were asked to do a check-in process in a hotel, where participants dealt with FLE and FSR (Figure 3.20) in two conditions: act neutrally and using innovative cues. In this experiment, the results showed that there were no differences between consumers' perception toward FSR when compared to their perception toward FLR. In addition to the positive impact of the innovative cues on human-robot and human-human interaction.

Figure 3.20 FSR and FLE in Service Encounter

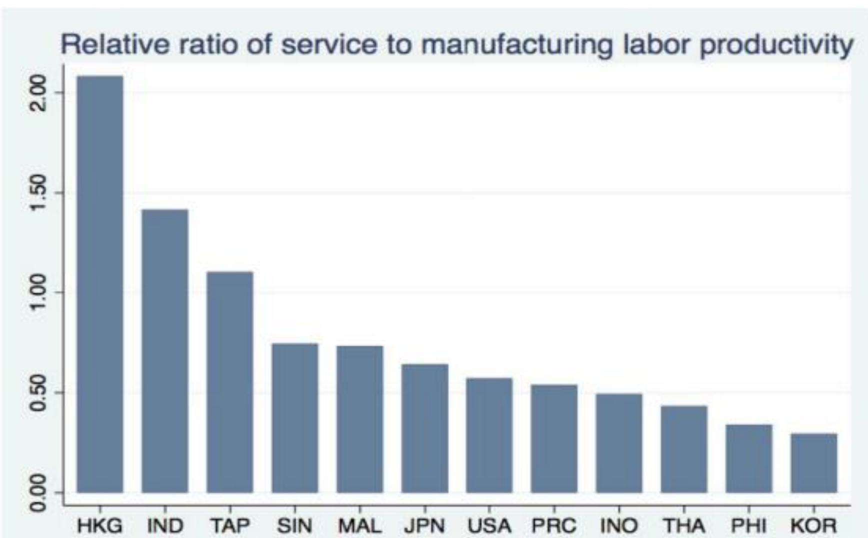
Source: (Stock & Merkle, 2018, p.7)

Chapter 4: Service Management

4.1 Introduction

The service sector is considered as the largest sector of the economy, especially in the western world, and it is growing fast. Also, it is the main source of job opportunities when compared to other sectors (Sheehan, 2006). For instance, the overall growth of the economy in Asia is associated with the performance of the service sector. Because, as the economy grows, the service sector becomes larger. But, the lower productivity in the service sector when compared to the industrial sector will impact negatively the overall growth, especially when the service sector size becomes bigger than other sectors. As shown in Figure 4.1, the growth of the service labor productivity in 2005 was lower than industrial labor productivity in Thailand, the Republic of Korea, and the Philippines. While, in Hong Kong, India, and Taiwan, service labor productivity was higher than the industrial labor productivity (Lee & Mckibbin, 2018).

Figure 4.1 Ratio of Service to Manufacturing Labor Productivity in 2005



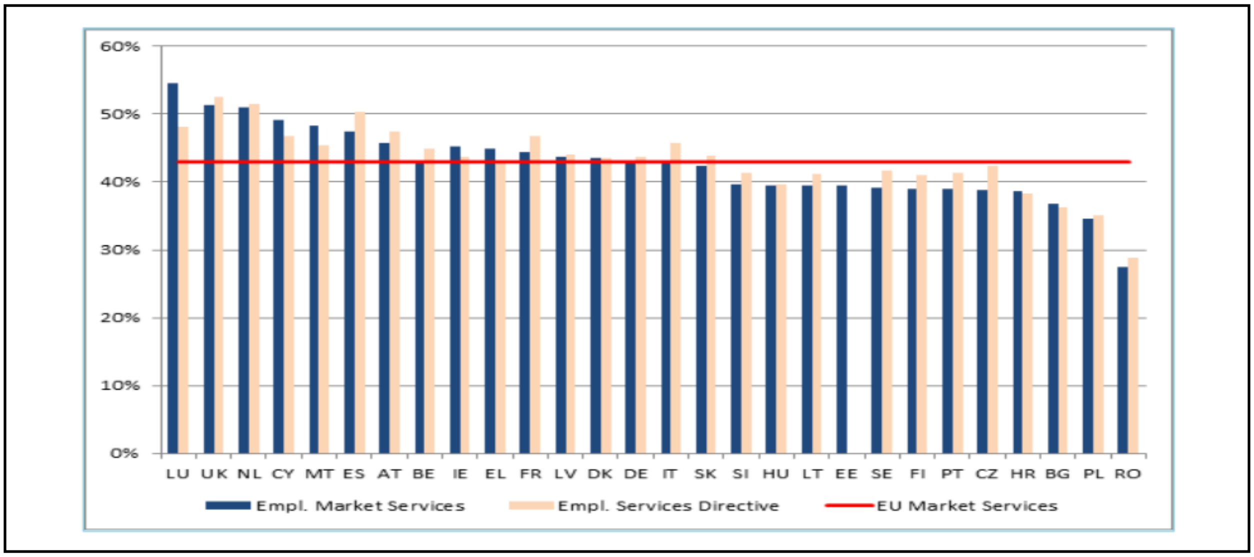
Source: (Lee & Mckibbin, 2018, p.251)

Furthermore, in the USA, the service sector is representing 79% of private-sector gross domestic product (GDP) and 80% of the employment rate in 2009 (Ward, 2010). Haksever and Render (2013) claimed that the impact of the service sector in the USA economy could be summarized through the following five headlines:

1. **Employment rate**: the service sector acquiring the highest employment rate. It reached more than 84% in 2016. In other words, the trend is going toward service jobs.
2. **GDP**: in 2016, the service sector produced more than 82% of the USA GDP, which is evidence of the continuous growth in the service sector.
3. **New business establishment**: almost 73% of new private organizations in the USA are classified as service organizations.
4. **International trade**: the balance between goods and services exportation has been increased from 1960 toward the service sector.
5. **Contribution to the industrial sector**: the relationship between the industrial and service sectors is complementary and interacted. Each sector is supporting the other. For example, transportation, advertisement, communication, and banking are some of the services that support the production and selling of manufactured goods.

Moreover, in the European Union (EU28), the service sector is considered the main contributor to employment and economic growth. The value-added share of the service sector is rising. For example, Luxembourg (70%), Cyprus (62%), United Kingdom (60%), and Greece (55.6%) were recorded the highest rates of the value-added. While, the Czech Republic (42.6%) and Hungary (44%) and Germany (48.5%) were among the lowest rates. Regarding the service sector contribution to the employment rates, Figure 4.2 shows the employment share of the services market for the EU28 countries (European Semester, 2014).

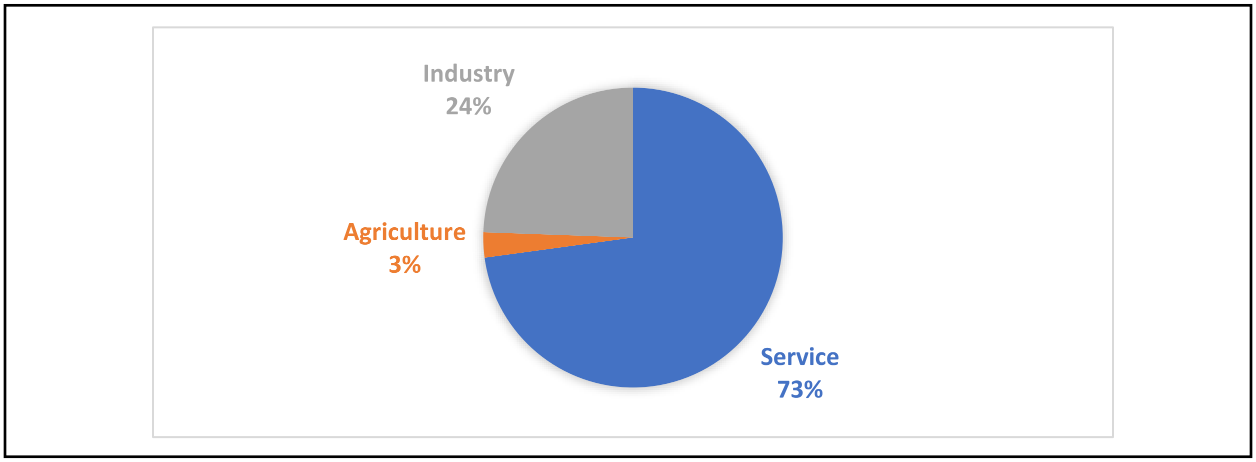
Figure 4.2 Employment Share (%) of Market Services in 2014



Source: (European Semester, 2014, p.2)

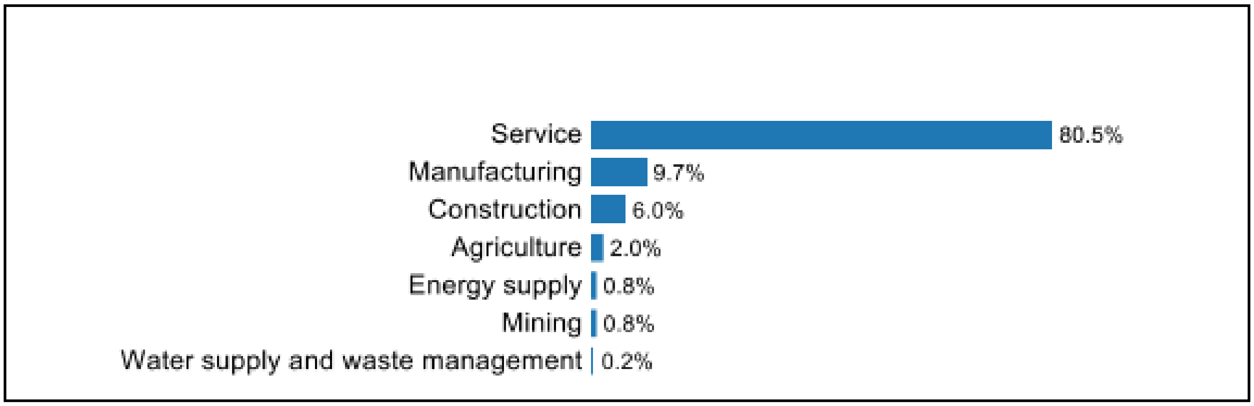
In Jordan, which is considered as one of the smallest economies in the Middle East, its economy is dominated by the service sector (Idris, 2016), which is representing 70% of GDP in 2010 as in Figure 4.3, and 80% of employment rate in 2012 as in Figure 4.4 (SNAP, 2014).

Figure 4.3 Jordanian GDP by Sector



Source: (SNAP, 2014, p.4)

Figure 4.4 Employment per Sector 2012



Source: (SNAP, 2014, p.6)

4.2 Service Definition and Conceptualization

Actually, the term service means intangible economical activities that can't be transformed or even stored, which are offered to the consumers by the service providers. Transportation, tourism, healthcare, and education are some examples of services (Zeithaml, Parasuraman, & Berry, 1985). Besides, the intangibility; variability, inseparability, and perishability are the characteristics that distinguish service from the physical products, which in turn makes a problem in the definition and evaluation of service quality in the marketplace (Tse & Wilton, 1988; Bebko, 2000). Here is some explanation of the service characteristics:

- **Intangibility**: it is considered a critical characteristic of the service when compared to the goods. It represents the inability to see, feel, taste, or touch the service before acquiring it (Bateson, 1979; Rossi, 2016).
- **Variability:** also, it is called heterogeneity and it is related to human performance, which makes it difficult to produce uniform outcomes. But also, it could be applied to the goods as the performance of the machines will vary from producer to producer. Moreover, this characteristic indicates the inability of standardizing the service when compared to the goods (Vargo & Lusch, 2004).
- **Inseparability**: it is related to the impossibility of separating the production of service from its consumption. In other words, most of the services should be sold before they get consumed immediately (Wilson, Zeithaml, Bitner, & Gremler, 2000; Vargo & Lusch, 2004).
- **Perishability:** it is related to the inability of producing and storing services, in order to be used later on (Andrés, González, & Sanz, 2015).

The perceived service quality is related to the differences between consumers' perception and their expectations regarding a certain service quality (Parasuraman, Zeithaml, & Berry, 1985a). Consumers can compare what they got and what they expected. As much as there are similarities, as much as consumers become satisfied (Boulding, Kalra, Staelin, & Zeithaml, 1993). Grönroos (1984) developed a service quality model by measuring the perceived service quality, based on technical quality, functional quality, and company image. The technical quality is related to what consumers get, and functional quality is related to how they will get the service. Moreover, technical quality is associated with consumers' evaluation of the delivered service by the comparison between their expectations and actual service performance. And the company image has a significant impact on the consumer perception of service quality (Yarimoglu, 2014). Parasuraman, Zeithaml, and Berry (1988) developed the SERVQUAL instrument to assess the consumer perception of the service quality that is offered by the service providers, which was driven from the service quality model for Parasuraman, Zeithaml, and Berry (1985b). The model is including the following dimensions: access, communication, competence, courtesy, credibility, reliability, responsiveness, security, tangibles, and understanding/knowing the consumer. Which then reduced to the following SERVQUAL instrument dimensions (Parasuraman et al., 1988, p.23):

1. **Tangibles**: physical facilities, equipment, and appearance of personnel.
2. **Reliability**: ability to perform the promised service dependably and accurately.
3. **Responsiveness**: willingness to help consumers and provide prompt service.
4. **Assurance**: knowledge and courtesy of the employees and their ability to inspire trust and confidence.
5. **Empathy**: Caring and individualized attention that an organization provides to its consumers.

For instance, when a salesperson shows a high level of empathy, assurance, and responsiveness, the consumer satisfaction level could be increased, which in turn could increase their attitude toward the offered product (Stock & Hoyer, 2005). In this context, empathy is related to understand consumers' perspectives and interact with them emotionally (Davis, 1983). Furthermore, tangibles are considered important in terms of employees' appearance and the degree of technology advancement that is deployed in healthcare facilities, for instance (Purcarea, Cheorghe, & Petrescu, 2013). However, patients draw more attention to personal skills, appearance and the perceived quality of service while choosing the primary care doctor (Bornstein, Marcus, & Cassidy, 2000), interpersonal skills, gender, and clinical competence are affecting female choice decision among physicians (Mavis et al., 2005), and surgeon reputation, competence, and quality of service are rated important for choosing surgeons (Yahanda, Lafaro, Spolverato, & Pawlik, 2016).

In the service sector, human capital is playing a crucial role in the success and continuity of service organizations. Human capital refers to knowledge, education, experience, personal skills, and competencies of employees (Dzinkowski, 2000; Namasivayam & Denizci, 2006). The employees’ role includes hiring their skills during direct interaction with consumers, especially during the purchase process. Because, the intangibility of the service makes employees skills as an important factor in the consumer persuasion of buying the service (Vomberg, Homburg, & Bornemann, 2015). Liao and Chuang (2004) claimed that employee performance is playing a vital role in business outcomes through its direct impact on consumer satisfaction. As the consumers feel happy with the frontline employee, as they may become more willing to make the purchase decision, which in turn could increase the positive outcomes. And the employee positive performance considered a competitive advantage for service organizations. Namasivayam and Denizci (2006) mentioned that, another major role for the frontline employees is to transfer the value to the consumers, especially when direct interaction between employees and consumers is involved, such as in airlines, hospitality, and healthcare services. As well, the authors advised that the employee characteristics (e.g. empathy and promptitude) should be taken into the consideration during the hiring process, as they have a major influence on the consumers perception of the service value.

Vroom (1964) developed the expectancy theory, which proposed that the behavior is a result of choosing among alternatives to minimize pain and increase pleasure. He pointed to the knowledge, skills, and abilities as the main determinants of employee performance. The theory has the following components:

1. **Expectancy**: it is about the relation between effort and performance. As per the expectancy theory, the employee beliefs that the increased effort will enhance the performance. It is affected by employee skills, knowledge, experience, available resources, and management support. Chiang and Jang (2008) mentioned that, when employees are highly motivated, they will work hard to improve their job quality and performance.
2. **Instrumentality**: the reward or the valuable outcome that is associated with performing the task. It is related to employee expectations. Instrumentality is affected by:
    - Trust in the decision-makers who will decide who deserves a specific outcome, based on the performance.
    - Control on the decision that is associated with who deserves a specific outcome.
    - A clear understanding of the polices**,** which is related to the correlation between performance and outcomes.
3. **Valence**: is related to the value of the outcome, and from the employee perspective. For instance, one employee may consider the money as a valuable outcome, another one may consider the promotion is the required outcome.

Vroom (1964) proposed that motivation is determined by expectancy, instrumentality, and valence. He believed that motivation is the explanation of why people choose a specific behavior or action (Lee, 2007).

Consumer loyalty can increase revenue, besides its important role in attracting new consumers through positive recommendations about a specific service. These recommendations will help the organization to strengthen its reputation in the long run, which makes it necessary for organizations to invest well in those consumers. Hence, the importance of the frontline employee is emerged in building a trust relationship between consumer and service providers, to meet consumer needs and expectations. Also, frontline employees and due to their direct contact with consumers can examine the engagement degree of the consumers toward their organizations. The employee-consumer interaction is playing an important role in consumer satisfaction and in creating consumer engagement (Cambra, Melero, & Vázquez, 2014).

The frontline employees' impact on service quality can be shown through the following values and beliefs, which are related to the term "Professionalism" and as mentioned by Lee (2014):

1. **Knowledge pursuance**: a good reputation can be achieved by maintaining a good level of knowledge and skills, which could be gained through education, training, and experience (Evetts, 2011).
2. **Sense of calling**: it is related to self-actualization by making the job as a part of employee life (Hall & Chandler, 2005).
3. **Consumer orientation**: it is related to the extent of attention that the employees are showing to their consumers (Stock & Hoyer, 2005).
4. **Self-management**: it is about the evaluation, decision making, assessment, and discretionary judgment that the employee can undertake, especially in complicated situations.

Furthermore, frontline employee service competencies could have a direct impact on consumer perception of service quality (Wu, Tsai, Hsiung, & Chen, 2015). The competence can be defined as employee characteristics that produce a distinctive performance in a given task (Spencer & Spencer, 1993). Rainsbury, Hodges, Burchell, and Lay (2002) classified the competences into:

1. **Hard skills:** these are connected to the technical side of performing the job and considered as cognitive skills and dependent on the employee Intelligence Quotient (IQ). Knowledge and technical skills are representing the minimal level that is required to execute the job with basic competence.
2. **Soft skills:** which are concerned with the personal characteristics of the employee, including interpersonal and behavioral skills. It is associated with the Emotional Quotient (EQ) (Kemper, 1999).

Wu et al. (2015) defined frontline employee competences as a combination of professional and interpersonal competencies that are required to perform the tasks successfully when serving consumers. They claimed that employees can enhance their service competences and can expedite their career development in the workplace by training. Also, they claimed that managers need to perform training courses and establish a reward system for their employees to improve these competencies.

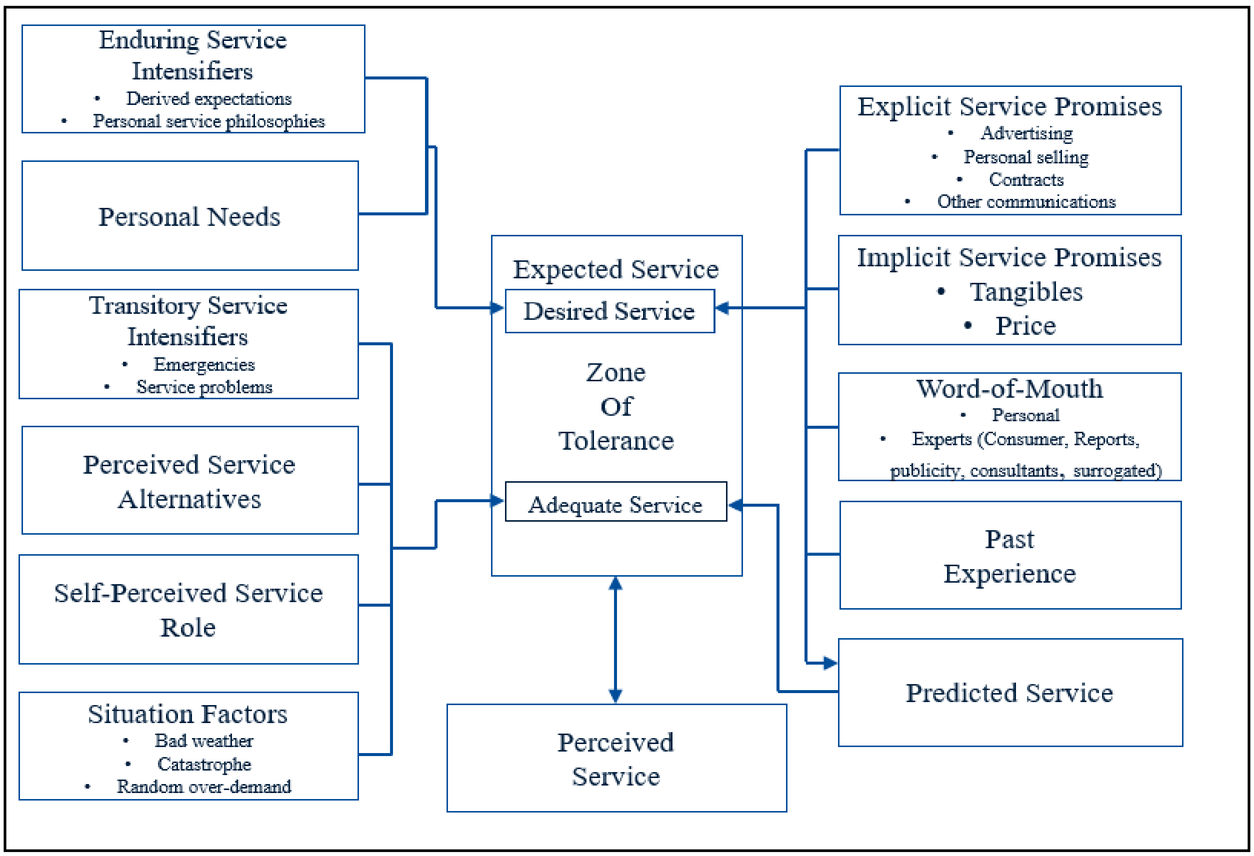
4.3 Service Quality and Expectation Models

Consumers build their judgment on service quality based on the comparison between their expectations and actual performance of perceived service. Once the performance gets closer or exceeds expectations, the consumer becomes more satisfied (Tse & Wilton, 1988). The Expectancy-Disconfirmation Paradigm (EPD) model proposed that, when the service performance matches consumer expectations, confirmation is the result. However, when there are differences between consumer expectations and service performance, disconfirmation is the result, positively or negatively, and based on the direction of the disconfirmation (Oliver, 1977, 1980). Which mean, when the service performance exceeds consumer expectations, positive disconfirmation will occur, and consumer, in turn, will get satisfied. Contrariwise, consumers will become dissatisfied when negative disconfirmation occurs as a result of negative differences between service performance and consumer expectations. Also, confirmation between consumer expectations and service performance will lead to consumer satisfaction (Yuksel & Yuksel, 2008). In addition to that, consumers are willing to modify their expectations upon their perception of the delivered service. They will increase their expectations once they get positive disconfirmation, and they will lower the expectations in the situation where negative disconfirmation is the result (Brickman, 1972; Tam, 2005). Different types and definitions of consumer expectations have been developed across the literature. For instance, some authors sort these expectations into six groups: ideal, predictive, adequate, deserved, normative, and desired expectations (Santos & Boote, 2003). The ideal expectations (wished to) refer to the excellent or perfect standard that represents the highest level of expected performance. The predictive expectations refer to consumer calculations regarding what the performance will be. Adequate expectations (Minimum tolerable) are representing the minimum accepted level of service performance. As well, deserved expectations are related to consumer investment. In other words, it is related to the balance between cost and service performance, and from the consumer perspective (Miller, 1977). Normative (Should be) expectations are related to consumers' beliefs regarding what the service should be offered, in terms of performance. It is almost formulated based on suppliers' promises about service quality to attract consumers (Parasuraman et al., 1985). And finally, desired expectations are defined as how consumers want service to perform (Swan & Trawick, 1980). Zeithaml, Berry, and Parasuraman (1993) defined desired expectations similar to the ideal expectations. Despite that, it could be seen as a combination of what consumers believe about what it could be and what it should be (Santos & Boote, 2003). In the same context, while studying consumers behavior in shopping streets, Medrano, Olarte-Pascual, Pelegrín-Borondo, and Sierra-Murillo (2016) classified ten types of expectations into four groups: comparison (Normative, equitable “or deserved” and predictive expectations), ideal amount (Vector and ideal point expectations), levels (Desired and adequate expectations) and point of assessment approach (Pre-encounter and intra-encounter expectations). Their work was focused on comparison approach, and more specifically on the normative and predictive expectations. The normative expectations are related more to how the suppliers want to show themselves to their consumers in terms of offered service performance. And the predictive expectations are related to what consumers expect from the service provider.

In the same context, Zeithaml et al. (1993) developed the consumer expectation model (Figure 4.5). Three types of service expectations were developed in the model: predicted service, desired service, and adequate service expectations. The authors claimed that consumers evaluate service quality based on their desire and what they considered acceptable. Also, desired and adequate services are separated by a tolerance zone. Regarding the tolerance zone, it differs from consumer to consumer and it could be increased or narrowed for the same consumer. Moreover, they proposed the following relations: (1) adequate service level is more changeable than the desired one, (2) the desired service level is assessed by the enduring service intensifiers, (3) the relation between consumer need level and desired service level is positive, (4) adequate service level will be expanded and the tolerance zone level will be retracted in the presence of transitory service intensifiers, (5) as consumer perceive the existence of service alternatives, the adequate service level will be increased and the tolerance zone will be decreased, (6) the adequate service level increases with the increase in the self-perceived service role, (7) the adequate service level gets narrowed and the tolerance zone get expanded temporarily with the situational factors, (8) the adequate service level gets expanded and the tolerance zone gets narrowed with the higher predicted service level, (9) desired service level and predicted service level gets higher as the explicit service promises get higher, (10) desired service level and predicted service level get increased with the implicit service promises, (11) desired service level and predicted service level gets increased with the positive word of mouth and (12) there is a positive relationship between previous experience and desired service level, and between previous experience and predicted service level. Finally, the authors classified consumer evaluation into two types:

- **The superiority of perceived service**: which is a result of the comparison between perceived service and desired service.
- **Adequacy of perceived service:** This is a result of the comparison between perceived service and adequate service**.**

Figure 4.5 Consumer Service Expectation Model



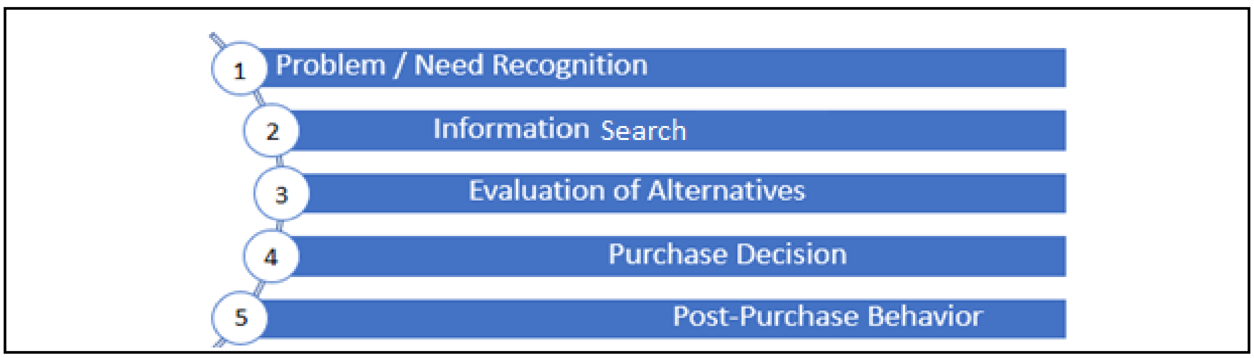
Source: (Zeithaml et al., 1993)

The consumer service expectation model pointed to the following proposed gaps: **GAP1**, where service quality evaluation by the consumer is affected by the gap between consumer expectations and management perception of those expectations. For **GAP2**, the consumer viewpoint of service quality will be affected by the gap between management perception to the consumer expectations and the company specifications of service quality. In **GAP3**, consumer perception of service quality will be affected by the gap between service quality specifications and quality of delivered service. Also, in **GAP4**, consumer perception of service quality will be affected by the gap between the actual quality of delivered service and the external communications about the quality of service. And finally, in **GAP5**, consumer perception of service quality is a function of the direction and size of the gap between perceived service quality and expected service quality.

4.4 Service Choice Decisions: How Service is Chosen by Consumers?

The decision-making process in choosing, purchasing and using any product is important not only to consumers but also to organizations to understand how consumers will choose a specific product, especially when many alternatives are available and from different organizations (Bettman et al., 1991). Based on Engel, Blackwell, and Miniard (1995) model, the decision-making process includes the followings stages (Figure 4.6):

Figure 4.6 Decision-Making Process Stages



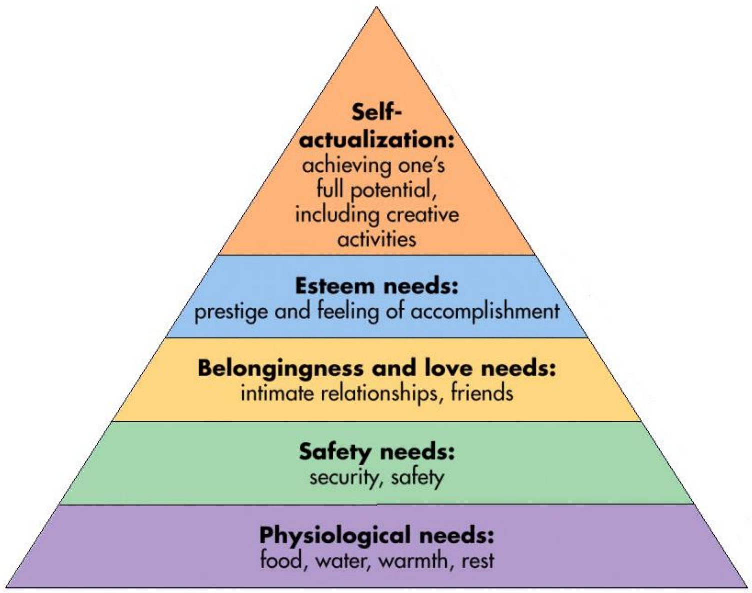
Source: (Engel et al., 1995)

1. **Problem/Need recognition**: it is the first step toward the purchase decision, and it is called also a problem identification. It is described as "the perception of a difference between the desired state of affairs and the actual situation sufficient to arouse and activate the decision process" (Engel et al., 1995, p.176). Furthermore, it includes the consumers' recognition of their need to perform a purchase (O'Keefe & McEachern, 1998). The need could be divided into functional and psychological needs. The functional need is related to product performance, and the psychological need is about consumer emotions. Moreover, the need could be introduced from internal or external stimuli. The internal stimuli are represented by Maslow's hierarchy of needs, which is shown in Figure 4.7 (Maslow, 1943). While, the

external stimuli could be a result of attractive advertisements or recommendations from family members and friends (Munthiu, 2009). Engel et al. (1995) defined two factors influencing the need recognition:

- **Environmental influences,** which include culture, social class, personal influences, family, and situation.
- **Individual differences,** which include consumer resources, motivation and involvement, knowledge, attitude, personality, values, and lifestyle.

Figure 4.7 Maslow's Hierarchy of Need



Source: (Maslow, 1943)

2. **Information search**: In this stage, the consumers will start looking for more information about the products to meet their needs (O'Keefe & McEachern, 1998). The source could be internal or external. The internal source is from memory and previous experiences with a specific product. While, the external one is through products advertisements, searching over the internet, asking advice from friends or family members, and so on (Munthiu, 2009). The organizations in this stage should draw more attention to promoting their products through the communication channels, such as websites, brochures, and e-word of mouth (Bucatariu & George, 2017). Kotler and Keller (2014) categorized the information search into four groups:

   a) **Personal**: family members, neighbors, and friends.

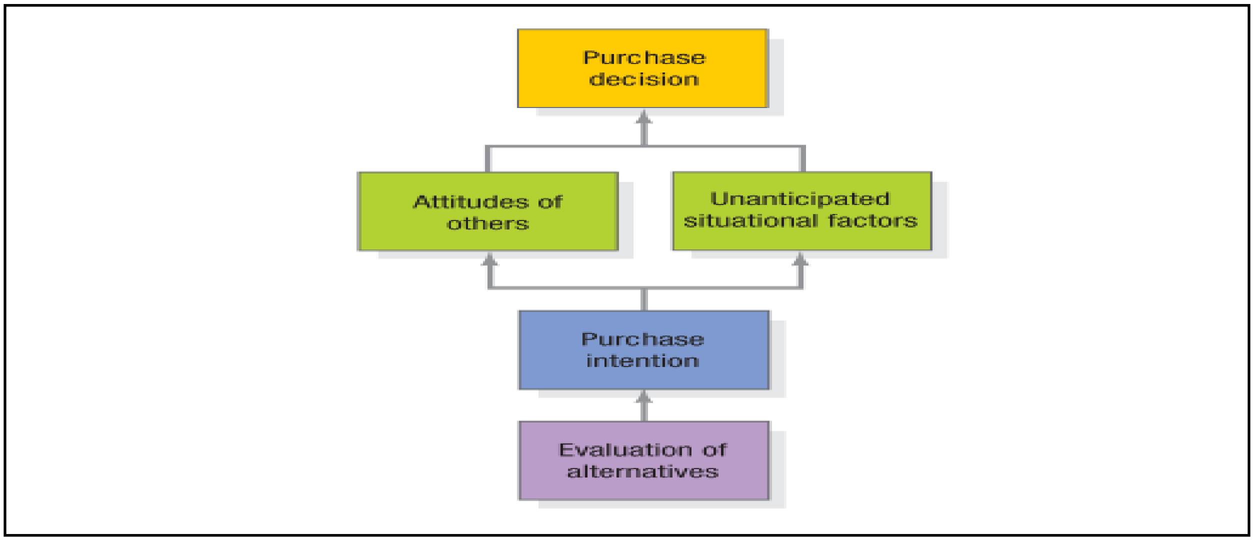
b) **Commercial**: websites, salespersons, distributers, advertisements, and packaging.
c) **Public**: blogs, rating organizations, and social media.
d) **Experiential**: product use, handling, and examining.

3. **Evaluation of alternatives**: in this stage, the consumer will process the information from previous stages to sort specific products. It may be considered the most important stage in the choosing criteria process (Bucatariu & George, 2017). Munthiu (2009) mentioned in his research five factors affecting the evaluation process: consumer experience, the risk associated with the decision, product value to the consumer, the easiness of alternatives' evaluation process, and the urgency of the decision. Accordingly, the evaluation process will lead to a set of beliefs and attitudes toward different brands. Belief is defined as "a descriptive thought that a person holds about something", and attitude is defined as "a person's enduring favorable or unfavorable evaluations, emotional feelings, and action tendencies toward some object or idea" (Kotler & Keller, 2014, p.168; Krech, Crutchfield, & Ballachey, 1962). As per the Expectancy-Value (EV) model, the attitude toward a specific product is determined by consumer belief about it. This means, each product is associated with a specific attribute caused by each belief. Based on the EV model, the overall attitude toward any product is determined by the subjective values or the associated attributes for that product, and by the degree at which these attributes are related (Fishbein & Ajzen, 1975).
4. **Purchase decision**: The purchase intention is formulated after the evaluation stage and before the purchase decision. Furthermore, the attitudes of others (i.e. social influence) and situational factors are intervening in the path between intention and actual decision as shown in Figure 4.8 (Kotler & Keller, 2014). Engel et al. (1995) categorized the purchase decision into three types:
   a. **Impulse purchase**: the choice is done inside the store or sales point.
   b. **Partially planned purchase**: the product is already chosen, while the brand or service provider will be chosen upon visiting the store.
   c. **Fully planned purchase**: the consumers are already decided which product and brand that they will choose.

All the purchase decision types could be influenced by situational factors, such as product promotion, company reputation, salesperson treatment, perceived risk, price, etc. (Lee, 2005).

5. **Post-purchase behavior**: in this stage, the consumer will be satisfied if the performance of the product is as expected, besides the positive perceived value (i.e. quality to price relation). A satisfied consumer means positive recommendations about the product to others and re-purchase behavior. However, the dissatisfied consumer will affect negatively the company image by negative recommendations, which are unfortunately spread faster than the positive ones (Kotler & Armstrong, 2012). In services, service quality, physical environment, and perceived control over service delivery are important factors that contribute to consumer loyalty (Grewal, Iyer, Gotlieb, & Levy, 2007). In some service settings, such as in healthcare, it is difficult for the consumer to evaluate the service. The positive belief about the service provider, the efficiency of the service provider, and the positive perceived physical environment could enhance consumers' perception of service quality. Also, it is important to reduce the perceived risk before, during, and after the delivery of service (Gummesson, 2004).

Figure 4.8 Steps Between Evaluation and Purchase Decision



Source: (Kotler & Keller, 2014, p.170)

In fact, the consumer decision-making process could be generalized for both goods and services in different contexts. However, in terms of service selection criteria, which are a part of the consumer decision-making process, they may vary according to service nature. For instance, in healthcare, anxiety seems to be more important than the psychological or physical risk in assessing service quality (Lanjananda & Patterson, 2009). Furthermore, the criteria that consumers use while assessing hospitals are based on the quality of care, specialized services, price, reputation, cleanness, appearance, quality of personnel behavior, accessibility, and word of mouth (Taylor & Cosenza, 1999; Bucatariu & George, 2017). Another example is car maintenance service providers. Brito, Aguilar, and Brito (2007) pointed to the following choice criteria: employees' appearance, the image of being reliable, general equipment condition, general site condition, attendants' cooperation, willingness to negotiate, price, and willingness to solve consumer problems. While, in hospitality services, price, service quality, and flexibility could be the most important factors affecting the choice. In this context, the service quality is represented by aesthetics of the restaurant/hotel, employees interpersonal skills, and knowledge (Verma, Plaschka, & Louviere, 2002). Finally, in the educational sector, the cost is considered as one of the important factors influencing the choice of high educational institutions (Padlee, Kamaruddin, & Baharun, 2010). Another important factor is the reputation of the educational institution. Nowadays, ranking institutions over internet (e.g. QS World University Rankings, Academic Ranking of World universities) give directions to students regarding the global reputation of the target institution, which help them during the choice decision process (Sabir, Ahmad, Ashraf, & Ahmad, 2013).

In general, peoples' emotional responses are formulating their decisions and moral views (Romportl, 2015). Also, emotions have a major role in influencing intention behavior. That means the behaviors could be stimulated or even eliminated based on people's perception of a specific emotion (White & Yu, 2005). Furthermore, expected emotions are crucial in the decision-making process, because they impact attitudes toward a certain behavior (Bechara, 2000). In general, positive emotions are associated with positive results, and negative ones are associated with negative results (Babin & Babin, 2001). Mehrabian and Russell (1974) and Russell and Mehrabian (1977) introduced the three factor-theory for emotions. they used three dimensions to represent emotions: Pleasure, Arousal, and Dominance dimensions (PAD). Pleasure and arousal were defined in the previous chapters. While, dominant is related to the extent at which individuals feel that they are controlling or controlled by a stimulus (Kulviwat et al., 2007; Mehrabian & Russell, 1974). But Russell and Mehrabian (1977) pointed to the importance of arousal and pleasure in defining the individual emotional state. Therefore, Russell (1979) suggested using arousal and pleasure dimensions to represent the emotions and without using the dominance dimension. Consistently, studies in marketing established the importance of arousal and pleasure, and dominance was neglected frequently (e.g. Das, 2013; Koo & Ju, 2010; Mummalaneni, 2005; Pelegrín-Borondo et al., 2015). In service settings context, emotions found to be a predictor of consumer satisfaction and behavioral intention. For instance, patients are using their emotions to decide whether to proceed or to terminate the service buying process. The positive behavioral intention is related to the positive perception of arousal and pleasure, and the service rejection is related to the negative ones (Ladhari & Rigaux-Bricmont, 2013; Ladhari, Souiden, & Dufour, 2017). In online games too, consumers' intention and use behavior are related to the perceived emotions. Designers have to consider the stimulation of the positive emotional state of the users to grantee the expected and the long-term use of such games (Huang, Ali, & Liao, 2017). Even in bank services, employees are playing a critical role in formulating and establishing the positive emotional state of their consumers toward bank services, which could impact positively the intention and use behavior toward these services (Allard, Babin, Chebat, & Crispo, 2009).

Chapter 5: Consumer Behavior and Technology: Technological Acceptation Models

5.1 Theory of Reasoned Action (TRA) and Theory of Planned Behavior (TPB)

The Theory of Reasoned Action (TRA) was developed by Fishbein and Ajzen (1975), to explain the relationship between attitude, behavioral intention, and actual behavior. The authors defined the model constructs as followed (Fishbein & Ajzen, 1975):

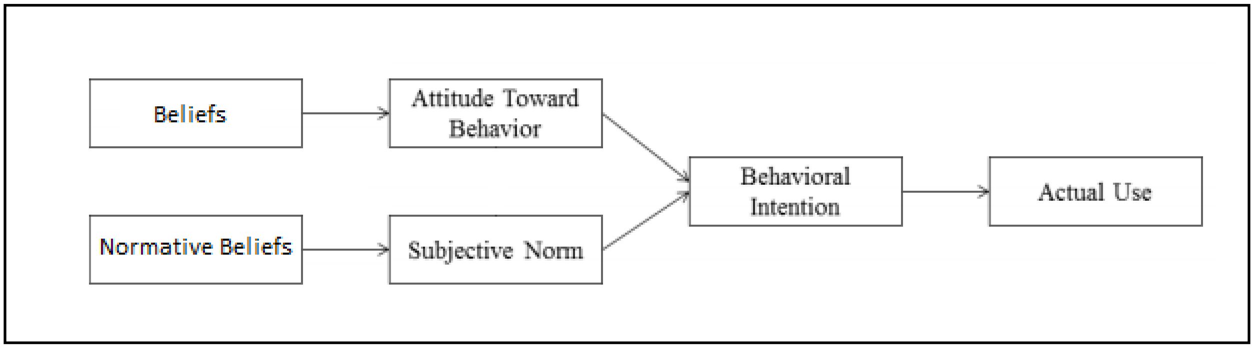
- **Attitude toward behavior**: the humans' positive or negative evaluation of a specific behavior.
- **Social influence**: The person's perception of doing a specific behavior based on the opinion of other important people.
- **Behavioral intention**: The person's subjective probability to perform a specific behavior.

As per Fishbein and Ajzen (1975), individuals can learn or form beliefs about an object from observations, outside sources of information, or inference from different processes. These beliefs will represent the basis of their attitude, intention, and actual behavior. So, individuals' attitude towards any object is associated with their beliefs about the same object. Then, the attitude to that object is associated to do different behaviors, which are related to the same object. Thereafter, each specific intention is connected with specific behavior. However, attitude and actual behavior could stimulate a new belief through the feedback process.

In parallel, normative beliefs, which are a result of reference group beliefs about doing or not doing a behavior, will lead to formulating the social influence, which in turn will affect the intention and the actual behavior of individuals. In sum, the actual behavior is affected by attitude and social influence that are related to this behavior. And the relation is mediated by the intention toward the same behavior. The TRA model is shown in Figure 5.1.

Sheppard, Hartwick, and Warshaw (1988) claimed that the TRA model found to be a good predictor of behaviors, but it is weak in goal situations. On the other hand, even the model has been developed to investigate the intention to perform a single behavior, it showed the best performance in situations where the consumer has to choose among different alternatives. In fact, the success of TRA theory is related to the degree at which the behavior is under volitional control. As a result, TRA components are not sufficient to predict behavior when volitional control is reduced (Glanz, Rimer, & Viswanath, 2008). Furthermore, using the intention to predict behavior will not be accurate if the behavior needs some skills to be performed, like knowledge, resources, or experience (Sheppard et al., 1988).

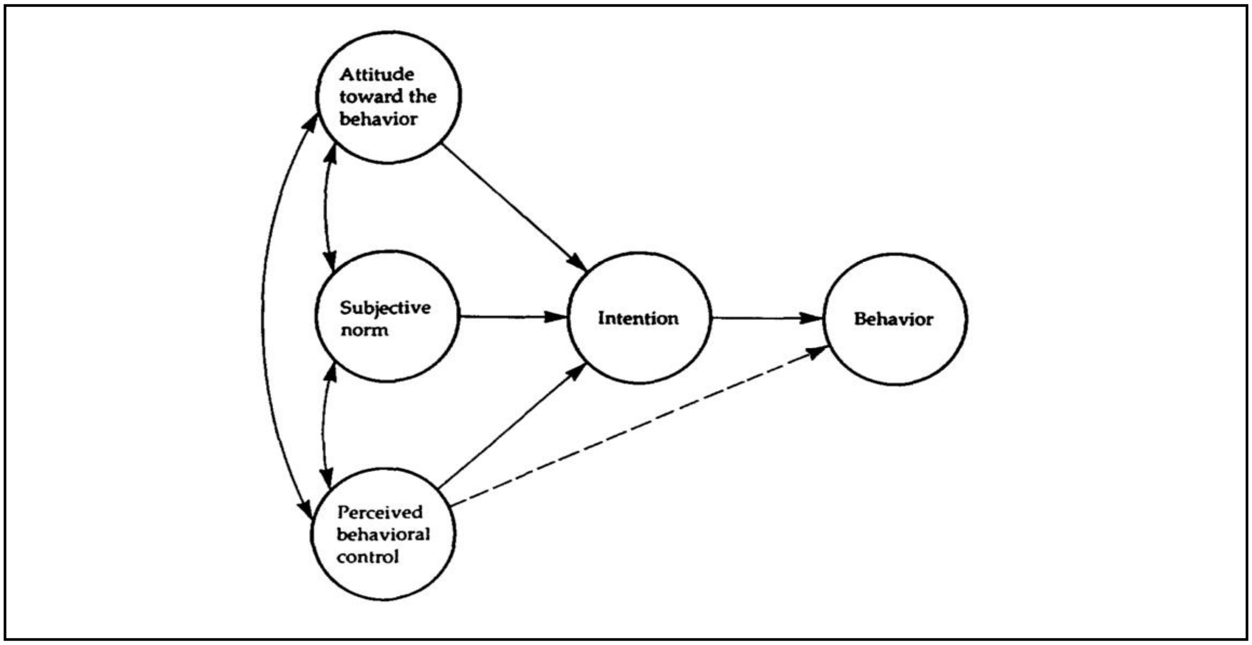
Figure 5.1 TRA Model



Source: (Fishbein & Ajzen, 1975, p.16)

To be able to predict the behavior in conditions where volitional control is incomplete, Schifter and Ajzen (1985) extended the TRA by adding a new construct to the model, which is the perceived behavioral control, to predict behavior intention and thus the actual behavior. By adding this construct, Ajzen (1991) introduced the Theory of Planned Behavior (TPB), as shown in Figure 5.2. In this theory, the perceived behavioral control, social influence, and attitude are the independent determinants of behavioral intention. Where the perceived behavioral control refers

Figure 5.2 TPB Model



Source: (Ajzen, 1991, p.182)

to “people’s perception of the ease or difficulty of performing the behavior of interest” (Ajzen, 1991, p.183). Control beliefs are the determinant of perceived behavioral control, which defined as “a set that deals with the presence or absence of requisite resources and opportunities” (Ajzen, 1991, p.196). Whilst, the normative beliefs, which are the determinant of the social influence, are related to the importance of the referent individuals or groups' acceptance or rejection to perform a specific behavior (Ajzen, 1991).

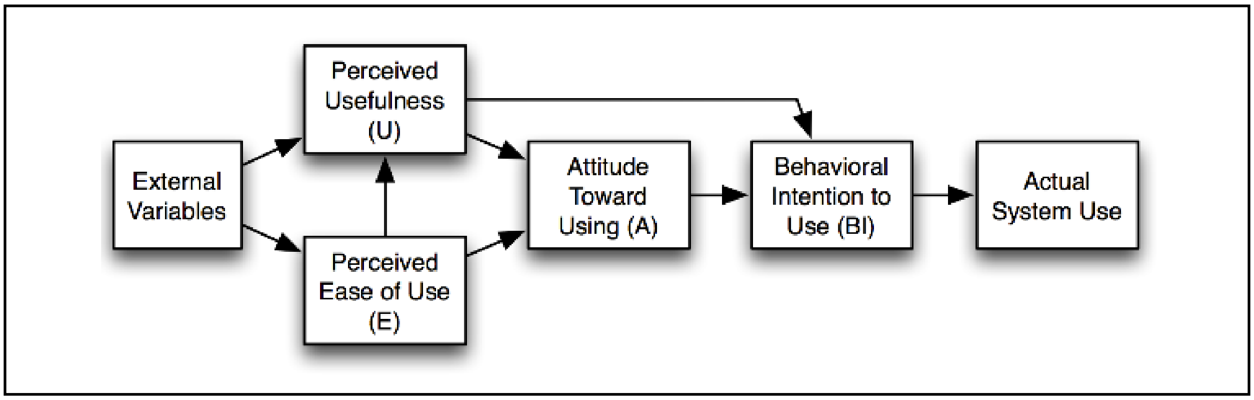
As per TPB, the execution of any behavior is a combination of intentions and perceived behavioral control. To get an accurate prediction, many conditions should be met. Firstly, the measures of intention and perceived behavioral control must match or compatible with the predicted behavior. Secondly, during the assessment and observation interval of the behavior, perceived behavioral control and intention have to remain stable. Thirdly, prediction of behavior from perceived behavioral control should realistically reflect actual control (Ajzen, 1991). Nevertheless, the limitations of this theory are related to the need and the emotional factors, which were ignored by the authors. As some scholars claimed, in some situations, individuals will be involved in a specific behavior because of their need to do that, even if they have a negative attitude. Also, individuals may not be involved in another behavior, because they don’t need to do that, even if they have a positive attitude toward this behavior. Also, emotions could affect beliefs and other model constructs (Sniehotta, 2009).

5.2 Technology Acceptance Model (TAM, TAM2, and TAM3)

The Technology Acceptance Model (TAM) is a theory that has been extended from TRA by Davis (1985). He used two factors affecting information technology (IT) adoption: Perceived Usefulness (PU) and Perceived Ease of Use (PEU). These two factors are influenced by external variables, such as organizational training and design features of the IT system. On the other hand, PU and PEU are affecting the attitude towards using the system. Moreover, the PU and attitude are affecting the behavioral intention towards using the system. And finally, the behavioral intention has a major impact on the actual use of that system.

This theory is offering a brief way to model the impact of the external variables on beliefs, attitudes, and intentions. External variables could be anything outside persons’ control. For example, the design features of any IT system, which offer different functionalities that can improve the work better than other systems, could influence the PU positively. Furthermore, training that is offered by the company on the system use, could influence the person PEU positively, which in turn may influence the adoption of that system. As Davis (1985) claimed, the model was developed to provide a theoretical framework for design and implement the IT systems, by improving the understanding of the user acceptance process. This also could help the designers to evaluate their systems before the implementation process. The TAM1 model is shown in Figure 5.3.

Figure 5.3 TAM1 Model

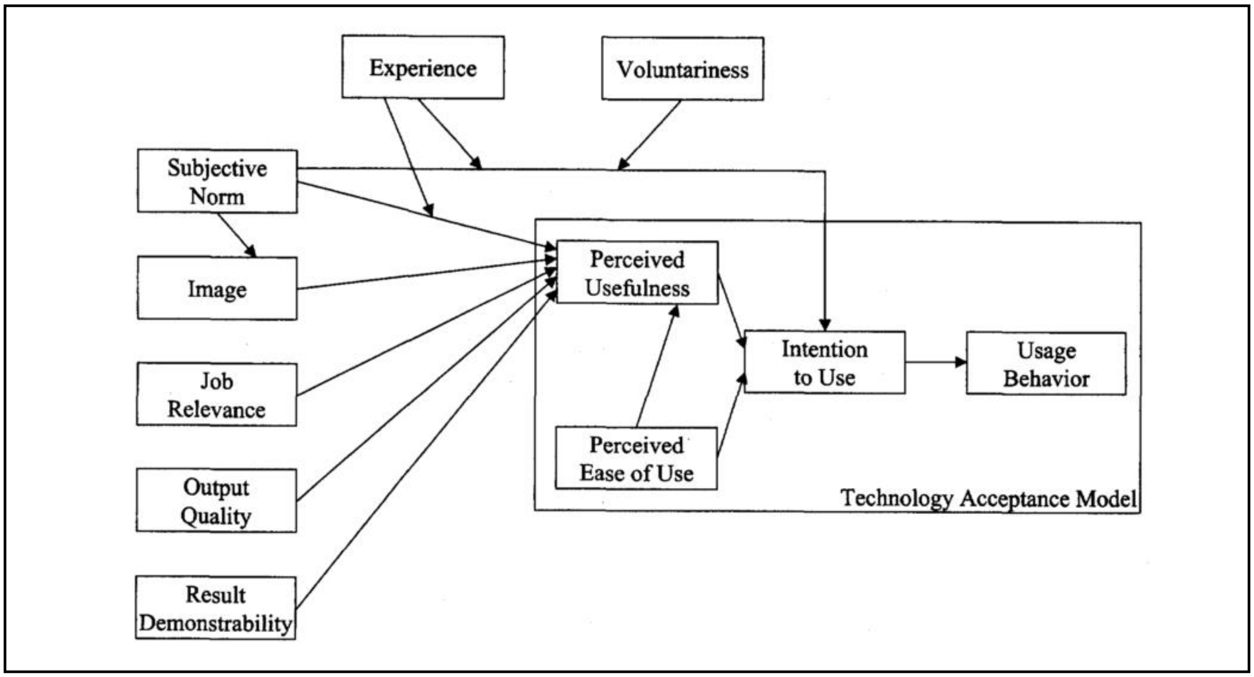


Source: (Davis, Bagozzi, & Warshaw, 1989, p.985)

PEU didn't show a significant impact on attitude and intention in some fields. For example, in physician's intention to use telemedicine technology (Hu, Chau, Sheng, & Tam, 1999), mobile commerce drivers (Wu & Wang, 2005), and attitude towards e-shopping (Ha & Stoel, 2009). Some of the previous researchers claimed that TAM lacks adequate accuracy and relevance that can make it a reliable theory for technology acceptance studies (Chuttur, 2009). Lunceford (2009) mentioned in his research that the framework of PU and PEU missed other factors, such as job duties and cost, which may impose users to adopt the new technology. Besides that, many efforts were done by different researchers to expand TAM, in order to make it consistent with the changing IT environments, which has led to a condition of theoretical confusion, where it isn't clear which version of TAM is the compatible one (Benbasat & Barki, 2007).

Due to the limitations of TAM in the context of explaining the factors that make a person perceive new technology as useful, Venkatesh and Davis (2000) introduced the TAM2, which is an extension of the original TAM, by adding new variables that work as determinants of PU. In TAM2, social influence has been used as a predictor of PU with image, experience, voluntariness, and cognitive variables (i.e. job relevance, PEU, output quality, and result demonstrability). Also, it has a direct impact on the behavioral intention with voluntariness and experience. Whereas, the attitude towards use was extracted from TAM2. Markedly, TAM2 enabled the authors to give more details for explaining why users are finding any system useful. Mainly, TAM2 is compatible with both, voluntary and mandatory work environments, except for social influence, which has an effect on the mandatory work settings but hasn't on the voluntary ones. TAM2 model is shown in Figure 5.4.

Figure 5.4 TAM2 Model



Source: (Venkatesh & Davis, 2000, p.188)

Here are the definitions of some of the TAM2 variables:

- **Voluntariness:** is defined as "the degree to which use of the innovation is perceived as being voluntary, or of free will" (Moore & Benbasat, 1991, p.195).
- **Image**: is defined as "the degree to which use of an innovation is perceived to enhance one's image or status in one's social system" (Moore & Benbasat, 1991, p.195).
- **Result Demonstrability:** is defined as "the tangibility of the results of using the innovation" (Moore & Benbasat, 1991, p.203).
- **Output Quality:** is referring to "how well the system performs the job tasks" (Venkatesh & Davis, 2000, p.191).

- **Job Relevance:** is defined as "an individuals' perception regarding the degree to which the target system applies to their job" (Venkatesh & Davis, 2000, p.191).

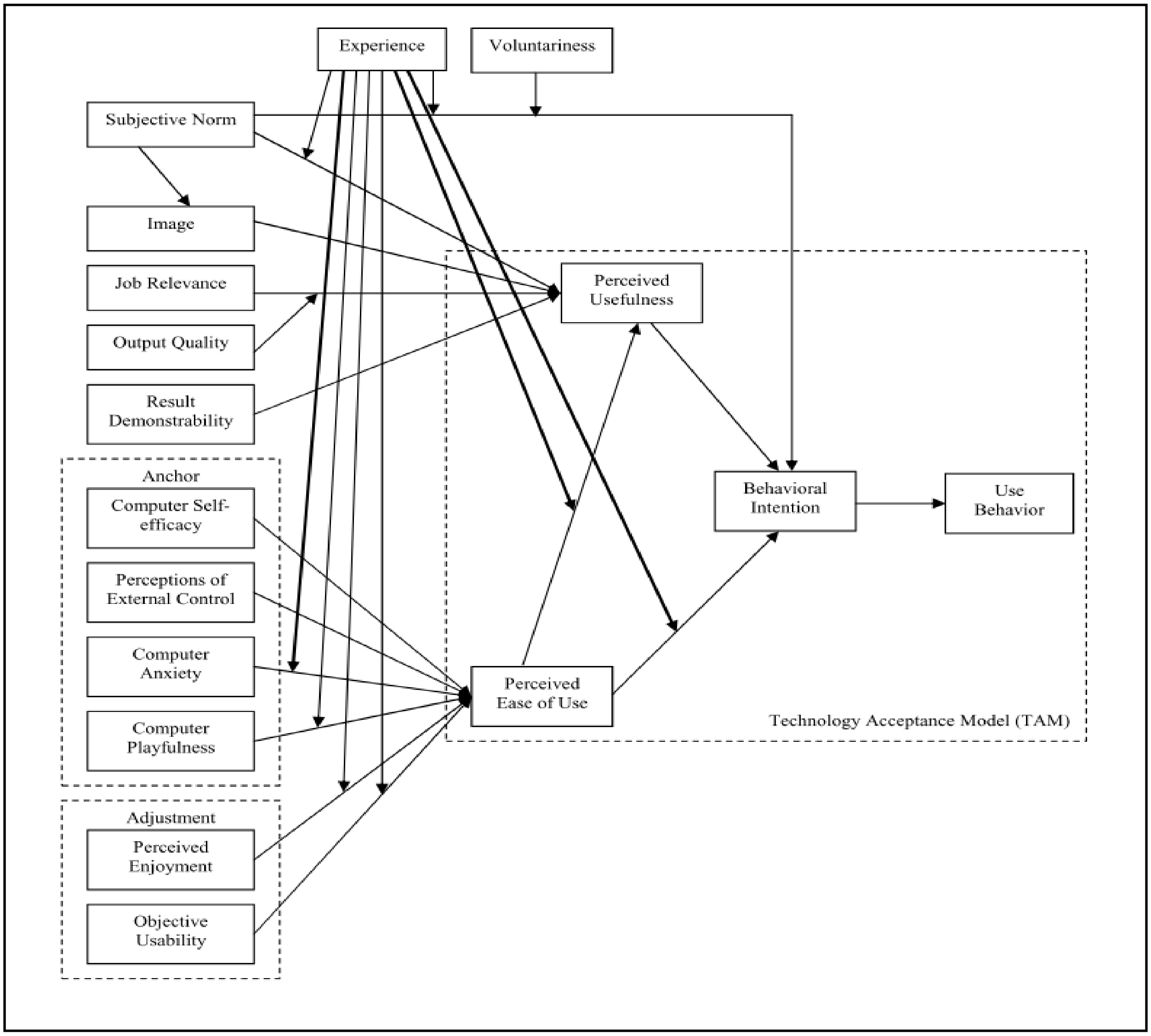
Admittedly, the voluntariness is moderating the relation between social influence and behavioral intention. Because the relation between social influence and behavioral intention is significant in the mandatory system when compared to a voluntary system. Whilst, the intention to use a new voluntary system is strongly determined by PEU and PU when compared to social influence. In other words, the relation between social influence and behavioral intention isn't significant when the job setting is voluntary (Hartwick & Barki, 1994). Whereas, the relationship between social influence, PU, and behavioral intention is moderated by the experience. For the first time use, people will refer to others opinion (i.e. social influence) when they are forming their first belief about a new system, but when they gain experience with using the system and identify its strengths and weaknesses, the effect of social influence will decrease (Venkatesh & Davis, 2000).

The last version TAM3 was developed by Bala and Venkatesh (2008) by adding new constructs into TAM2, as shown in Figure 5.5, where the anchor and adjustment constructs have been integrated into the model as determinants of PEU. And here are the definitions of these variables:

- **Computer Self-Efficacy**: The degree to which individuals believe that they can perform a specific task/job using the computer (Bala & Venkatesh, 2008, p.279).
- **Perception of External Control**: The degree to which an individual believes that organizational and technical resources exist to support the use of the system (Bala & Venkatesh, 2008, p.279).
- **Computer Anxiety**: The degree of "an individuals' apprehension, or even fear, when they face the possibility of using computers" (Venkatesh, 2000, p. 349).
- **Computer Playfulness**: The degree of cognitive spontaneity in microcomputer interactions (Webster & Martocchio, 1992, p. 204).
- **Perceived Enjoyment**: The extent to which "the activity of using a specific system is perceived to be enjoyable in its own right, aside from any performance consequences resulting from system use" (Venkatesh, 2000, p. 351).

- **Objective Usability**: A "comparison of systems based on the actual level (rather than perceptions) of effort required for completing specific tasks" (Venkatesh, 2000, pp. 350–351).

Figure 5.5 TAM3 Model



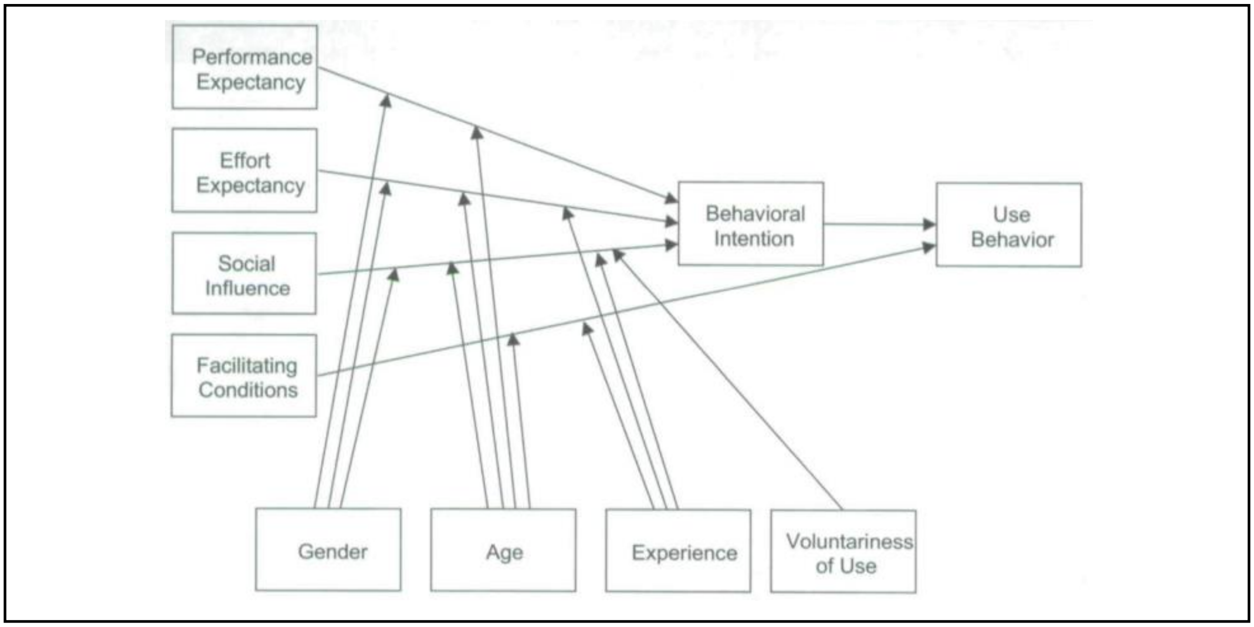
Source: (Bala & Venkatesh, 2008, p.280)

5.3 Unified Theory of Acceptance and Use of Technology (UTAUT and UTAUT2)

The Unified Theory of Acceptance and Use of Technology (UTAUT) is a model produced by Venkatesh et al. (2003), with four determinants of behavioral intention and use behavior (Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions), and four moderators of the key relationships (Gender, Age, Experience, Voluntariness to Use). The author aims from this model to explain user intention to use new information systems and dependent usage behavior of that system. The model is shown in Figure 5.6.

- **Social Influence:** is defined as "the degree to which individuals perceive that important others believe they should use the new system" (Venkatesh et al., 2003, p.451).
- **Facilitating Conditions**: are defined as "the degree to which an individual believes that an organizational and technical infrastructure exists to support the use of the system" (Venkatesh et al., 2003, p.453).

Figure 5.6 UTAUT1 Model



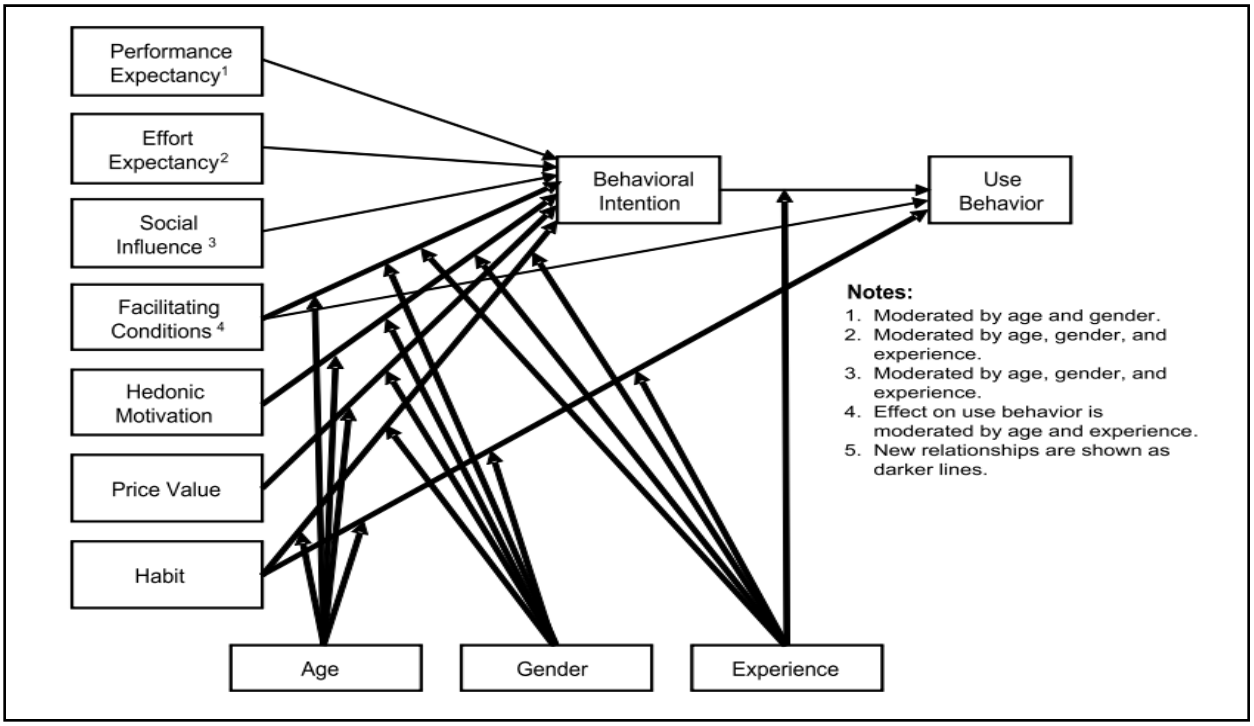
Source: (Venkatesh et al., 2003, p.447)

In UTAUT2, which was developed by (Venkatesh et al., 2012), new factors have been added to the original UTAUT1 model with some modification on the relation between its constructs. Hedonic motivation, price value, and habit have been integrated into the UTAUT1 to form the UTAUT2 (Figure 5.7). The new constructs are defined as below:

- **Hedonic Motivation**: is related to the fun or pleasure that is associated with the use of new technology (Brown & Venkatesh, 2005).
- **Price Value**: is defined as the consumer perception of the balance between the cost of using/hiring new technology and its perceived benefits (Dodds, Monroe, & Grewal, 1991).

- **Habit:** is defined as "goal-directed automatic behaviors that are mentally represented" (Aarts & Dijksterhuis, 2000, p.76).

Figure 5.7 UTAUT2 Model



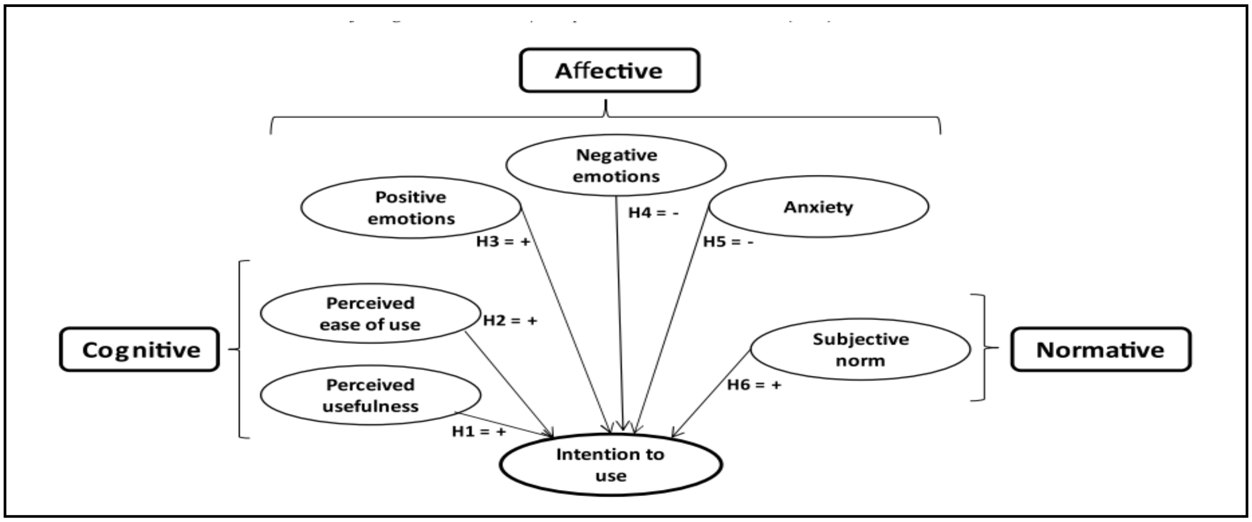
Source: (Venkatesh et al., 2012, p.160)

In summary, age, gender, and experience are moderating the effect of hedonic motivation on behavioral intention. Also, age and gender are moderating the impact of price value on behavioral intention. And finally, habit is affecting the usage behavior directly and through behavioral intention, but this effect is moderated by age, gender, and experience (Venkatesh et al., 2012).

5.4 The Cognitive-Affective-Normative Model (CAN)

The Cognitive-Affective-Normative model (CAN), which is developed by Pelegrín-Borondo et al. (2016) and Olarte et al. (2017), to explain the new technology acceptance, especially the intention to use the technological implants. The model has been built based on TAM and UTAUT models. The authors defined three types of variables (Figure 5.8): cognitive variables (PU and PEU), Affective variables (Positive emotions, negative emotions, and anxiety), and the Normative variable (Social influence). So far, the model has been tested in three contexts. In the first one, the model was introduced to analyze the differences in behavioral intention when end-users will use the implants for themselves, and when they will use the implants for their child's. The research result found that cognitive variables have a limited impact when the users are going to use the implants for themselves. But there is no impact in the case of using the implants for users' children. In addition, the results confirmed the importance of the normative variable on the intention to use. However, two of the affective variables (i.e. positive and negative emotions) impacted the intention to use, while the third one (i.e. anxiety) had no significant impact on the intention to use (Pelegrín-Borondo et al., 2016).

Figure 5.8 CAN Model



Source: (Pelegrín-Borondo et al., 2016, p.107)

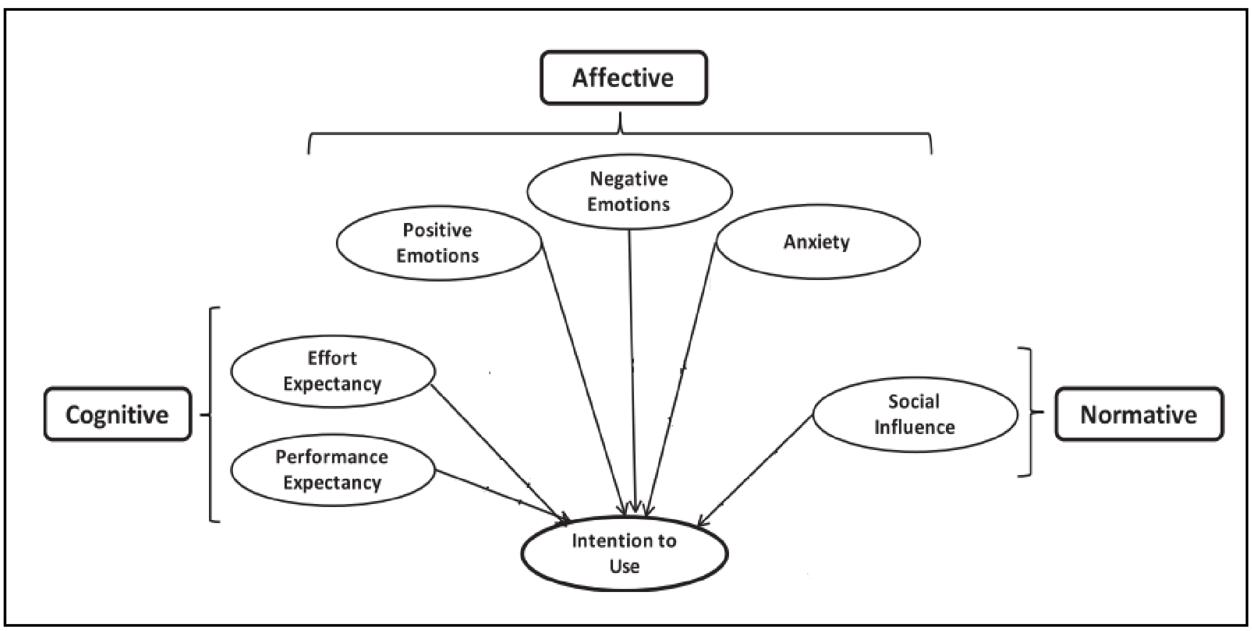
In the second context, the model was used to investigate the intention to use insideables (i.e. technological implants used to increase human innate capacity). For the affective variables, the positive emotions showed the most significant impact on the intention to use those insideables. While, the negative emotions showed the lowest impact. However, the anxiety didn't show a significant impact. The normative variable showed a significant impact on the intention to use insideables and it was in the second place behind the positive emotions. Whilst, the cognitive variables showed the lowest impact (Pelegrín-Borondo, Reinares-Lara, et al., 2017).

In the third study, Reinares-Lara et al. (2018) investigated the moderating effect of the ethics on the neural implants acceptance. They aimed to integrate the ethical factor as a moderator in the CAN model, to understand the acceptance of brain implants for increasing human capacities. In this research, the authors used performance expectancy and effort expectancy as cognitive variables instead of PU and PEU (Figure 5.9). The sample was segmented based on the ethical assessment of those technologies for three groups:

1. **Group 1**: ethically in favor.
2. **Group 2**: ethically against.
3. **Group 3**: ethically indifferent.

Positive emotion and social influence showed a strong significant influence on the intention to use the implants for all groups. Effort expectancy also showed a significant impact on the intention to use neural implants for all groups. Performance expectancy showed a low impact on group 2 and no influence on the others. The negative emotions showed an insignificant impact on all groups. However, anxiety was rejected because it had no significant effect. And finally, the effect of the ethical construct was rejected too. Even though the ethical evaluation of the implants helped in explaining the differences in the intention to use them, it didn't moderate the relation between the independent variables and the intention to use neural implants (Reinares-Lara et al., 2018).

Figure 5.9 The Updated CAN Model



Source: (Reinares-Lara et al., 2018, p.46)

Chapter 6: Proposed Model: Explaining Consumer Behavior about Service Choice among Humans, Robots, and Cyborgs

6.1 Introduction

In this chapter, this research will define the hypotheses and the model, which represents consumer choice criteria among human, robot, and cyborg services. Where the development of this model will be based on the direct interaction between consumers and employees, and on how employees can affect consumers' choice criteria. The proposed model will represent the common factors that can be applied to the three cases (i.e. human, robot, and cyborg).

With regards to the impact of human employees in consumer choice criteria, several studies in the literature have been investigating in this domain among different service providers and in several service settings. Also, they pointed to the factors related to the employee role in consumer choice and perception of service quality, such as in healthcare (Bucatariu & George, 2017; Lanjananda & Patterson, 2009), in financial services (Cagnina, 2016) and hospitality sector (Verma et al., 2002). As well, various studies have been conducted in the literature regarding the acceptance of robotic technology in different applications. In addition to many studies that have been focusing on human-robot interaction, as mentioned in the previous chapters. But what is important for this research is the use of the robot as an employee that has the ability to interact with consumers in such a way that it will be perceived positively. In fact, there are few studies in literature investigated in the consumer perception of robots in service settings, where the direct interaction with consumers is involved, as, for instance, in studying robots impact on consumers perception of hospitality service for Tung and Au (2018) and consumers perception of robots behavior while using it as a frontline employee and during the service encounter for Stock and Merkle (2018). Whilst, studies in cyborg technology acceptance are still in the early stages and investigating the acceptance to become a cyborg, not the acceptance of cyborg as an entity. This is understood because the technology itself is under development and people don’t know much information about the usability of this technology (Pelegrín-Borondo et al., 2016). Therefore, the proposed impact of the research variables on cyborg technology will be based on the nature of cyborg, which is a human with enhanced capabilities, caused by technology advancement.

6.2 Hypotheses

6.2.1 Effort Expectancy and Performance Expectancy

The previous studies about TAM models have confirmed their validity in studying the acceptance of different kinds of new technologies (Park & Pobil, 2013). The model cognitive constructs (i.e. PEU and PU) have been used in predicting robot acceptance (Broadbent, Stafford, & MacDonald, 2009; Smarr et al., 2012). In addition to UTAUT models constructs Performance Expectancy (PE) and Effort Expectancy (EE), which are related to PU and PEU (Alaiad & Zhou, 2013; Heerink et al., 2009b). Furthermore, some authors have been using these constructs alternately and considering perceived usefulness same as performance expectancy and perceived ease of use same as effort expectancy (Alaiad, Zhou, & Koru, 2013; Gao & Bai, 2014; Heerink, Kröse, Evers, & Wielinga, 2010a; Lee & Rho, 2013; Méndez-Aparicio, Izquierdo-Yusta, & Jiménez-Zarco, 2017; Phichitchaisopa & Naenna, 2013). This research will adopt the UTAUT constructs: PE and EE.

Even with the differences in the direction of the relation between EE, PE, and intention towards robotic technology in literature, most of the previous works are agreed about the importance of these constructs in predicting the acceptance of robotic technology. For instance, the intention to use companion and healthcare robots are affected positively by EE, especially in the early stages of the use (Heerink, Kröse, Evers, & Wielinga, 2008a, 2009a; Heerink et al., 2010a) and by PE, which is seen as a critical determinant of the long-term use of companion robots. On the other hand, the effect of EE on the intention to use robots was shown through its direct effect on PE only (Graaf et al., 2015; Park & Pobil, 2013). Nevertheless, some studies showed a significant impact of PE on the intention to use, and no impact of EE on both intention to use and PE (Conti, Nuovo, Buono, & Nuovo, 2015, 2017). In fact, all of these differences in the nature of EE and PE influence on the acceptance of robotic technologies don't affect their importance, especially when there is a direct interaction between humans and robots. For example, EE and PE showed a positive significant impact on the acceptance of robots as frontline employees in the service encounters, which points out the crucial role of these constructs on the human-robot interaction process (Mucchiani et al., 2017; Stock & Merkle, 2017). Whilst, the doubt is about the effect of these constructs on the acceptance of cyborg as an entity, since cyborg is an enhanced human. However, the technological side of cyborg can't be neglected while studying its acceptance. Therefore, it seems important to investigate the effect of PE and EE while interacting with cyborgs in terms of technology, based on the technological part of the cyborg. As aforementioned, previous studies about the acceptance of being cyborg has been investigating in the impact of both constructs. For instance, PE was shown as a strong predictor of the intention to use wearable technologies, but EE didn't show a significant impact (Nasir & Yurder, 2015). Furthermore, both constructs seemed to be critical to the intention to use Radio-Frequency Identification (RFID) implants (Werber, Baggia, & Žnidaršič, 2017, 2018), on the technological implants acceptance (Pelegrín-Borondo et al., 2016) and showed a positive impact on the acceptance of technological implants (Pelegrín-Borondo, Reinares-Lara, et al., 2017). Whereas, they are considered important for the acceptance of neural implants (Reinares-Lara et al., 2018).

But what if users don't perceive the usefulness and the simplicity of these technologies positively? Actually, the answer is associated with the importance of EE and PE constructs on the intention toward such technologies. While studying the acceptance of using new information technology in hospitals, Aggelidis and Chatzoglou (2009) pointed to the importance of the two constructs in the intention and use behavior toward this technology. The results showed that these constructs are the most important ones among other technology acceptance constructs. The negative perception of both of them will cause a rejection of such systems and keep the manual way in performing the tasks, which is dependable on human capabilities and skills. Kijsanayotin, Pannarunothai, and Speedie (2009) results were consistent with Aggelidis and Chatzoglou (2009) findings through studying the acceptance of information technology in Thailand's community health centers, except the degree of the importance between both constructs, where PE found to be more important than EE for the behavioral intention and use behavior. Opposite to these findings, Pai and Huang (2011) found EE the strongest predictor of the intention to use new technologies, because it has a direct impact and indirect impact through PE on the behavioral intention and uses behavior. In the electronic and online services, such as in healthcare and banking sectors, users are building their intention and use behavior toward these technologies based on the expected outcomes and simplicity of using them when compared to the traditional ways, where human is involved (Chen, Liu, Li, & Yen, 2013; Hendrikx, Pippel, Wetering, & Batenburg, 2013; Kuo, Liu, & Ma, 2013; Miao, Lu, & Shuai, 2014; Rho, Choi, & Lee, 2014; Saigí-Rubió, Torrent-Sellens, & Jiménez-Zarco, 2014). For instance, the acceptance of mobile health services is related to consumers' perception of PE and EE of those services. Nevertheless, the negative perception of these two criteria could result in a rejection of mobile health services and favoring human services instead (Guo, Yuan, Cao, & Chen, 2012; Lai, 2014; Lee & Rho, 2013; Sun, Wang, Guo, & Peng, 2013). Furthermore, patients are willing to use the telemedicine services, because they found it easy to use. However, they have doubts about their performance, which could make them reject it and insist on using traditional services (Abdullah et al., 2016). Performance and simplicity improvements require more attention and efforts from the service providers and the technology designers, in order to improve the success of these technologies, such as in healthcare robots (Alaiad & Zhou, 2014). Otherwise, users (Bawack & Kamdjoug, 2018), patients (Garavand, Samadbeik, Kafashi, & Abhari, 2017), or consumers (Wirtz et al., 2018) may reject the services provided by robots and cyborgs, and maintain their preferences towards human services. Therefore, this research assumption is laid between two scenarios. The first one is related to performance expectancy and effort expectancy toward the robot, cyborg, and human services, which possibly will affect the intention and use behavior positively toward them. The second scenario is related to the intention toward human services instead of robot and cyborg ones, in case consumers don't find robots and cyborgs useful and ease in terms of usage outcomes and simplicity when compared to the traditional services, where human is the dominant one.

H1a: Consumer intention to use among human, robot, and cyborg services is affected positively by Effort Expectancy.

H1b: Consumer intention to use among human, robot, and cyborg services is affected positively by Performance Expectancy.

6.2.2 Social Influence

Social influence is related to the influence of society members on individual behavior, and it was driven from Theory of Reasoned Action (TRA) and Theory of Planned Behavior (TPB) for Fishbein and Ajzen (1975) and Ajzen (1991), respectively. Social influence has been used to predict the intention and use behavior to use new technology in the TAM and UTAUT models, and it showed a significant impact on the intention and use behavior (Venkatesh & Davis, 2000; Venkatesh et al., 2003). In fact, the influence of friends and family members on the individual intention to use the robots seems to be significant, especially when there is a direct interaction between humans and robots (Conti et al., 2017; Heerink et al., 2009a). For example, the positive human-robot cooperation in work environments could be stimulated by positive advice and recommendations from others, who have a positive previous experience or convinced by the usability of robots as co-workers (Bröhl, Nelles, Brandl, & Mertens, 2016). Meanwhile, the expected role of social influence on the robot's acceptance in frontline jobs seems to be significant in positive ways (Wirtz et al., 2018) and on the acceptance of social robots by elderly people (Alaiad & Zhou, 2013; Alaiad et al., 2013; Chen, 2018).

Regarding cyborg technology, nothing is known about the interaction between humans and cyborgs. However, social influence presents itself as a strong predictor of the acceptance to become a cyborg, such as in predicting the intention to use breast augmentation among women (Moser & Aiken, 2011), its significant impact on the intention to adopt the wearable technologies in healthcare (Gao et al., 2015; Weng, 2016), its positive impact on the intention to use implants for both end-users and their child's (Pelegrín-Borondo et al., 2016) and its significant impact on using memory implants (Reinares-Lara et al., 2018). In general, negative social influence could inhibit the acceptance of any technology. In other words, when the influencers people had a bad experience with a specific product or service, they may recommend others to avoid using it (Olarte-Pascual et al., 2015).

In the human service context, people's influence on the choice criteria among different services could be shown as a recommendation from relatives and friends or influence from parents (Mokhlis, 2009). Usually, when consumers feel satisfied with the organization's services, they may recommend it to their relatives (Cronin, Brady, & Hult, 2000). For instance, people's influence showed a significant impact on student choice criteria among international universities through parents, relatives, and agents' recommendations (Mazzarol & Soutar, 2002). Furthermore, it is an important determinant in choosing retail banking (Cagnina, 2016). Moreover, it is critical to consider other people's recommendations seriously during the choice of healthcare institutions, doctors, and surgeons (Bornstein et al., 2000; Ejaz et al., 2014).

H2: Consumer intention to use among human, robot, and cyborg services is positively affected by the favorable Social Influence.

6.2.3 Emotions (Arousal and Pleasure)

Most people's decisions and moral views are a result of emotional responses (Romportl, 2015). Emotions have a major role in influencing intention and use behavior. This means, some emotions could encourage a behavior, and others may modify or eliminate it (White & Yu, 2005). Furthermore, expected emotions are crucial in the decision-making process, because they impact attitudes toward a certain behavior (Bechara, 2000). In general, positive emotions are associated with positive results, and negative ones are associated with negative results (Babin & Babin, 2001).

In the CAN model developed by Pelegrín-Borondo et al. (2016) and Olarte et al. (2017), in order to measure the intention to become a cyborg, the authors used the emotional dimensions: positive emotions and negative emotions. However, there is a certain consensus that the arousal and pleasure emotional dimensions are the most appropriate dimensions to analyze the emotional response of an individual to a stimulus (Pelegrín-Borondo et al., 2015). Being the level of emotional pleasure and the level of emotional arousal are the two emotional dimensions most supported by the literature (Cohen et al., 2008; Pelegrín-Borondo et al., 2015; Russell, 1980, 2003). In this sense, Mehrabian and Russell (1974) and Russell and Mehrabian (1977) suggested that you can measure what a person is feeling by employing a limited number of emotional dimensions. They proposed a scale with three dimensions: pleasure, arousal, and dominance (PAD). Eroglu et al. (2001) consider that "in many instances, the dominance dimension isn’t included, probably due to Russell's (1979) recommendation that the pleasure and arousal alone represent the range of emotion exhibited in response to environmental stimuli” (p.181).

In robotic technology acceptance, the interactive features of robots could enhance the emotional response of users, especially in social settings, where direct interaction between robots and humans is involved. For example, elderly people's intention toward social robots is strongly related to their positive arousal and pleasure feeling toward them (Zhang et al., 2010). The same effect was observed while using service robots in medicine delivery tasks. Robots' promotion of positive emotional responses toward patients could stimulate their acceptance of such technologies (Zhang et al., 2009). In general, arousal and pleasure found to be important in the attitude toward technology for both utilitarian and hedonic tasks (Kulviwat et al., 2007). It seems to be that, human emotional arousal and the expressed pleasure during the interaction with social robots could impact the intention and use behavior significantly, positively or negatively, and upon the human emotional state, which is associated with human-robot interaction (Damholdt et al., 2015). In the same context, perceived arousal and pleasure encourage behavioral engagement, such as in autism therapy using social robots (Rudovic et al., 2017). On the other hand, besides their impact on the intention and use behavior toward robots, positive pleasure and arousal emotions can improve performance, especially in the collaborative tasks between humans and robots. This is understood since positive emotions could motivate the human to enhance their performance by enhancing the human-robot interaction process (Jerčić et al., 2018). It is important to mention that, the effect of the emotional dimensions is observed more when interacting with affective robots (i.e. able to show emotions) than un-affective ones. Which in turn may affect the intention and use behavior toward such robots (Rudovic et al., 2017).

For human services, emotions role in explaining consumer behaviors has been established (Mattila, 2007). Therefore, emotions are playing a critical role in choosing the service providers and in stimulating consumer satisfaction (Gountas & Gountas, 2006). Barsade (2002) used the term "contagion effect of emotions". She claimed that the receivers will respond to the senders' emotional state, by imitating senders' facial expressions and cues and formulate their behavior and attitude upon that state. For instance, in bank services, when employees show positive emotions during service transactions, it may positively impact consumer mood and intentions (Tsai & Huang, 2002). Additionally, pleasure and arousal have an important role in gaining consumer satisfaction with bank services, in addition to their positive impact on the intention and use behavior (Das, 2013). Likewise, consumer emotions showed a significant impact on the intention to purchase through online services (Mazaheri, Richard, Laroche, & Ueltschy, 2014). As well, pleasure and arousal have a notable influence on the intention to choose among different hospitality service providers. This type of emotions should be stimulated by direct interaction with frontline employees and the perception of overall service quality (Lim, 2014). In the same context, these dimensions have a strong relation with service quality in healthcare services, where the positive perception of the services quality may positively impact patient emotions, which in turn could be positively reflected on the intention and actual choice of these institutions. And the role of employees is fundamental in service quality perception and positive emotions stimulation (Ladhari & Rigaux-Bricmont, 2013). Generally speaking, this type of emotions has a great influence on the intention and purchase behavior toward different types of products and services, and it could inhibit or motivate intention and purchase behavior (Pappas et al., 2013).

With regards to cyborg technology, the previous studies were focused on the impact of positive, negative and anxiety emotions on the intention to become cyborg (Olarte-Pascual et al., 2015; Pelegrín-Borondo, Reinares-Lara, et al., 2017; Pelegrín-Borondo et al., 2016; Reinares-Lara et al., 2018, 2016). However, not much is known about the impact of emotions on the acceptance of cyborg as an entity. Because of that, it makes sense to propose the impact of pleasure and arousal emotions on the intention to choose the offered services by cyborg, as it represents a combination of human-being and technology innovations.

H3a: Consumer intention to use among human, robot, and cyborg services is positively affected by Pleasure.

H3b: Consumer intention to use among human, robot, and cyborg services is positively affected by Arousal.

6.2.4 Perceived Risk

Perceived risk (PR) was introduced by Bauer (1960) to the marketing research area. It is related to the consumer perception of the uncertainty and adverse outcomes associated with buying a product or a service (Dowling & Staelin, 1994). Pavlou (2003) integrated the PR into the TAM model while studying the acceptance of e-commerce. The research results confirmed the direct impact of the PR on the intention and use behavior. In addition to the impact of the PR on the perceived usefulness of these technologies. While, different studies agreed with Pavlou's results regarding the impact of PR on the intention and use behavior. Meanwhile, they rejected the relation between PR and perceived usefulness (Faqih, 2013; Im, Kim, & Han, 2007; Lee, Park, & Ahn, 2001). In the same context, PR has been implemented in the UTAUT model and showed a strong effect on the intention and use behavior (Slade, Dwivedi, Piercy, & Williams, 2015), especially when the uncertainty exists in some new technologies and the associated behaviors with these technologies, such as in the online shopping (Chang & Wu, 2012), mobile health monitoring systems (Lee & Rho, 2013), electronic medical records exchange systems (Hsieh, 2014), and in studying personal cloud acceptance (Moqbel & Bartelt, 2015). Furthermore, the PR has been utilized in studying the intention towards using Near-Field Communication (NFC) technology for mobile payments, which is used to exchange data between payment devices and readers (Tan, Ooi, Chong, & Hew, 2014).

In the cyborg technology context, using PR in studying the acceptance of such technology could be justified, as the technology is still under development and not much is known about it. For instance, Gao et al. (2015) pointed to the significant negative impact of PR on the intention of using wearable technologies. However, Pelegrin-Borondo et al. (2017) found PR impact on the acceptance of insideable technologies higher than its impact on the wearable ones. Moreover, when benefits exceed the risk that is associated with nanotechnologies, the perception of risk decreases

(Gupta, Fischer, & Frewer, 2015; Satterfield, Kandlikar, Beaudrie, Conti, & Harthorn, 2009). Concerning robotic technology, different studies have been pointed to the importance of risk factors on the acceptance of these technologies. Nevertheless, the majority were contented with that pointing and didn't utilize the risk factor into their research models (e.g Destephe et al., 2015; Lilley, 2013; Matsui, Minato, Macdorman, & Ishiguro, 2018; Wirtz et al., 2018; Young et al., 2009). Whilst, Hancock et al. (2011) described how users will avoid the use of robots once they perceived the risk more than their perception of robot benefits. And Blut, Wünderlich, and Brock (2018) advised extending the conceptual models to include the PR while studying the intention toward using robots. Accordingly, this study believes in the importance of utilizing PR while studying the choice criteria among human, robot, and cyborg services.

H4: Consumer intention to use among human, robot, and cyborg services is affected negatively by the Perceived Risk.

6.2.5 Empathy

Empathy can be seen as the degree of caring and attention that employees show to their consumers (Parasuraman et al., 1988), and it has a direct impact on consumers' positive expectations toward service quality (Bebko, 2000). In addition to its role in establishing a successful consumer-employee interaction (Homburg, Wieseke, & Bornemann, 2009). Besides, it is related to understanding consumers' perspectives and interacting with them emotionally (Davis, 1983). In fact, empathy isn't a personal treat as much as it is a skill that can be created and developed to enhance consumer-employee interaction, which may lead to consumer satisfaction (Malle & Pearce, 2001). In the same context, Fugate, Kinicki, and Ashforth (2004) defined adaptability as employees' ability and willingness to modify their feelings, thoughts, and behavior to fit consumer requirements and needs, and it is related to employee empathy too (Kieren & Tallman, 1972). Furthermore, empathy should be taken into consideration during the hiring process, as it has a major influence on the consumers' perception of service value (Namasivayam & Denizci, 2006). For instance, when a salesperson shows a high level of empathy, the consumer satisfaction level could be increased, which in turn could increase their attitude toward the offered product (Stock & Hoyer, 2005).

In the human-robot interaction context, empathy showed a positive influence on human expectations toward robot behavior and on stimulating the interaction with it in service settings

(Niculescu, Dijk, Nijholt, Li, & See, 2013). Likewise, some researches in the literature refer to empathy as a component of robot social abilities. They considered it as a significant influencer on the intention to use social robots (Heerink et al., 2010b, 2010a; Smarr, 2013). Moreover, consumers perception of robot empathy could make them to see it useful, and motivate them to accept robots in their own environment (Torta et al., 2014) such as in healthcare services, where the perceived empathy showed a significant impact on the intention to use them (Conti et al., 2015), in social robots acceptance (Graaf & Allouch, 2013; Heerink, Kröse, Evers, & Wielinga, 2008b; Heerink et al., 2009a, 2010a) and it is considered important for elderly people care, who are suffering from different types of psychological and physiological problems and need special treatment (Broadbent et al., 2009). Likewise, empathy can overcome the negative outcomes of uncanniness (Heisele et al., 2002).

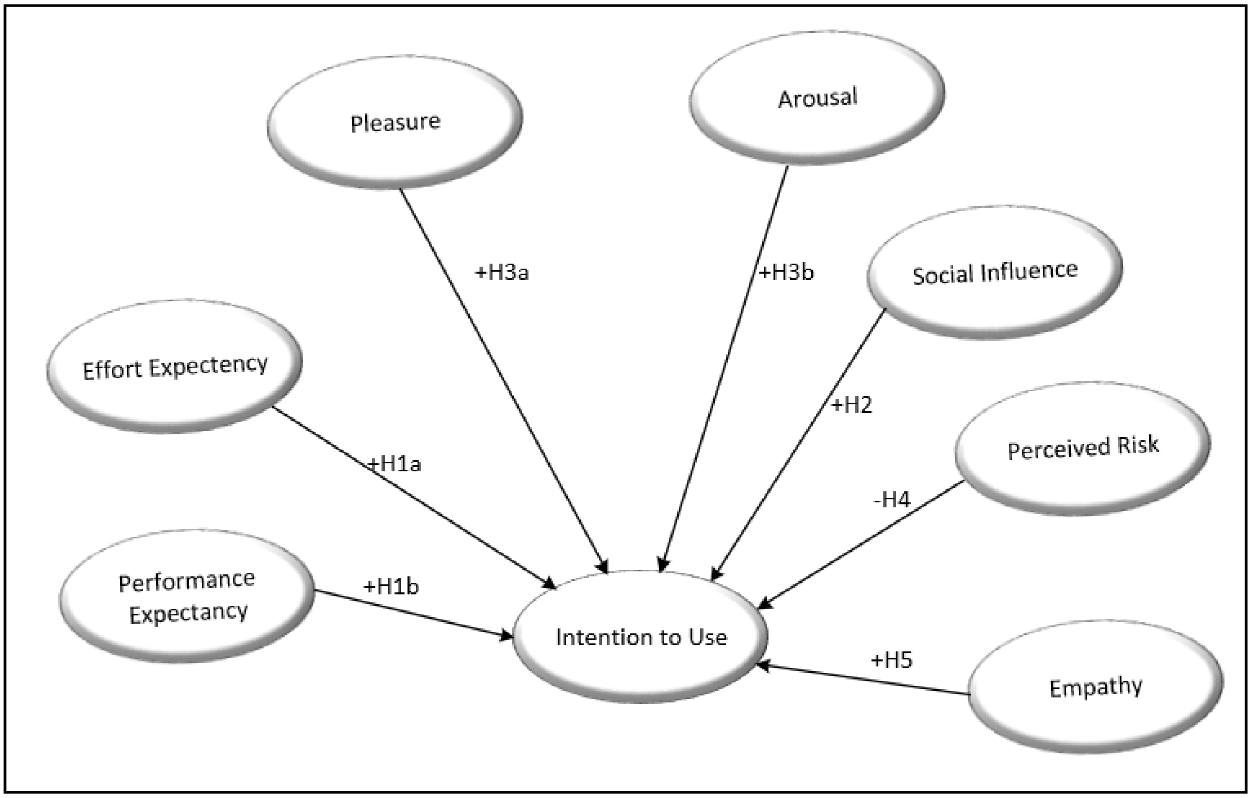
In fact, during human social communication, showing empathy could be considered as one of the main enablers of successful social interaction. Humans can convey empathy by imitating the facial expression of the other party (Riek & Robinson, 2008). It could be proposed that this way of conveying empathy should be used in the human-robot and human-cyborg interactions since the perceived empathy is found to be a significant determinant of the intention towards such technologies (Homburg & Merkle, 2019).

H5: Consumer intention to use among human, robot, and cyborg services is affected positively by Perceived Empathy.

6.3 Research Model

Figure 6.1, represents the theoretical model that explains the intention to use among humans, robots, and cyborgs services, which has been defined based on the aforementioned hypotheses.

Figure 6.1 | Theoretical Model of Acceptance of Robot, Cyborg, and Human Services



PART II: METHODOLOGY

Chapter 7: Consumer Behavior in the Emerging Technological Healthcare Sector: The Research Study

7.1 Research Scope and Rationale: A Study in the Healthcare Sector

The healthcare sector has been enduring challenges in countries around the world, distinctly more in developing countries, such as the increasing rates of population, aging, lifestyle infirmity, and the shortage of specialized personnel. Wherefore, efforts are endeavoring to improve the service quality, to enhance the performance, and to reduce the medical faults (Banna & Ottesen, 2018). One of the suggested solutions to these challenges is the adoption of new technologies and deploying them across the healthcare sector and among its different levels and applications. In this context, adopting the medical information systems to enhance patient's experience and healthcare services is considered as a necessity in developing countries. For instance, Jordan is the leader in healthcare tourism across Arab countries. The healthcare sector is attracting more than 250,000 foreign patients and generating around 1.2 billion USD annual revenue. According to the World Bank, the best healthcare services in the Middle East are offered by the Jordanian healthcare sector, which attracts patients across the region, especially from Iraq, Libya, Saudi Arabia, Sudan, and Yemen. Besides the highly skilled and educated labor force, bolster the use of new technology is considered one of the main factors supporting the good reputation healthcare services in Jordan (Innovation Jordan, 2020). Hence, it is expected that Jordan will acquire innovative technologies (e.g. robot and cyborg) once developed in its healthcare institutions to enhance the service quality and maintain its reputation among regional countries.

User's intention to keep using new technologies is unclear. In some cases, healthcare professionals are resisting the use of these technologies because they believe it is affecting the interactions with their patients and it is consequently impacting their work efficiencies negatively. This might be due to the lack of training and knowledge about the use and the outcomes associated with such technologies (Alsharo, Alnsour, & Alabdallah, 2018). Subsequently, most of the information systems and new technology acceptance researches are focused on why and how people are going to accept these technologies. And since there is a common complication between humans and technologies, the required investigations should be directed toward the factors that are affecting the successful adoption of these technologies (Alaiad et al., 2013). Furthermore, new types of technologies are emerging, which needs further and simultaneous investigations regarding the patient's perception of these technologies. For instance, the utilization of ubiquitous healthcare (u-healthcare) technology can improve healthcare services in terms of quality and availability, which refers to everywhere and anytime availability of medical services, such as home-care, mobile-care, and self-care. This kind of technology needs further investigations in order to identify the motivators and barriers towards accepting and adopting it (Jang, Kim, & Lee, 2016).

Since the last half-century, some robots have become integrated within the human daily life. What was considered science fiction, has now become a reality. The use of robots is increasing smoothly in most of the developed countries, and slowly in the majority of the developing countries. Robots have been developed for assisting and working with humans in social settings, such as in the workplace and at home. The use of companion robots to remind elderly people with their medication schedule or even for being engaged in physical exercises are representing examples of robots being used in human's social life. The expected interaction between humans and robots in the domestic environment could involve unstructured and informal ways, which may introduce new challenges of the successful deployment of these applications. Such challenges have motivated various research lines to investigate the factors affecting human-robot interaction quality and the acceptance of robots in the human own environment (Salem et al., 2015). They have been utilized frequently in the medical laboratory services and their usage has been increased in clinical and surgical applications (Hockstein, Gourin, Faust, & Terris, 2007). In fact, they have created a new positive paradigm in therapy techniques (Beasley, 2012). Also, medical robots' innovations lead to the emergence of different kinds of medical devices that can be used in local and remote robotic surgeries. The purpose of using these robots is to enhance and imitate human capabilities. So far, most of the available systems are used to support and improve surgeons' skills. Besides, they have also been used to increase the quality of life and patient's safety (Diana & Marescaux, 2015). Moreover, surgeons can use remote-controlled robotic arms at the console to operate laparoscopic surgeries, which has improved healthcare service quality, surgery success factors, surgeons' performance, reduce the stay period after the surgeries, and decrease the infection risks that could be associated with blood transfusion (Barbash & Glied, 2010). Nevertheless, recent and future studies are being aimed to develop systems that may replace both human physicians and surgeons (Hoeckelmann, Rudas, Fiorini, Kirchner, & Haidegger, 2015).

Undeniably, the diffusion of robotics applications is expanding rapidly and in a wide range of service sectors such as in education, bank services, tourism, hospitality, and healthcare services

(Tung & Au, 2018). Another example is healthcare robots, where the idea of using these robots is to improve healthcare quality and enhance patients' healthcare privacy inside their homes. Technology developers of these robots are promising to make the clinical information widely available at the right time and in the right place. Despite that, the acceptance of such technologies isn't associated only with healthcare institutions and robot designers, it is related more to consumers (patients) intention and willingness to accept and adopt robotic technologies in healthcare applications (Alaiad et al., 2013). In this context, robots need to be perceived as being useful and simple in terms of outcomes and use, to be accepted in social settings. Besides their ability to communicate and interact with human-being in natural ways. Meanwhile, the use of robots is shifted from being used by experts to be used by the public (Kirby, Forlizzi, & Simmons, 2010).

On the other hand, the integration between the human body and the environment becomes more explicit with cyborg technology (Wearables and Implants). The mutual shaping of environment, tools, and body gets more attention. The boundaries between human and machine are unclear as technology becomes close to being embedded within the human body (Britton & Semaan, 2017). For instance, some companies advise their employees to use the technological implants, which will offer them more abilities and replace the traditional ways of doing some daily activities, such as credit card payments and access control. The acceptance of such technologies can be used as evidence of the possibility of accepting technological implants and the acceptance of being Cyborg (Gauttier, 2018). Another example is the implantation of radio frequency identification devices (RFID). This device can transmit data numbers as pulses, which may represent PIN codes to be used for credit cards and doors access (Warwick, 2016). Meanwhile, humans' interests in reinforcing their emotional, cognitive, and physical abilities are seen as a common dream among most of the human-being individuals, which is associated with improving the quality of human life. Some types of enhancements are already available through surgeries, wearables, pharmaceutical compounds, and technological implants. Based on their use, some of these enhancements are already accepted by society, such as surgeries, wearables, and pharmaceuticals. Whilst, the acceptance of technological implants is still under investigation. The innovation in biomedicine, genetics, robotics, and nanotechnology are making it possible to produce hybrid bodies that combine biological and technological parts (Kostrica, 2018; Triviño, 2015). Also, reducing the size of the electronic component has consequently introduced

Nanotechnology, which makes it possible to think about creating small devices that can be implanted inside the human body for improving human physical and cognitive capabilities. Such devices are called nanoimplants or insideables (Pelegrín-Borondo et al., 2016; Reinares-Lara et al., 2016). Using insideable technologies by healthy people for increasing their innate capabilities was perceived as science fiction. However, in reality, the market already has different types of such innovative and growing technologies. The expectations regarding the cyborg market are promising for reputable new businesses with a potentially significant impact on the future of the technology industry and human societies (Pelegrín-Borondo et al., 2018). As per Pelegrín-Borondo et al. (2017), the use of physical and technological implants to compensate the physical disabilities and increase attractive power is already accepted by society. And the technological implants for increase innate human capacity are partially accepted and further investigations are being established to formulate a complete picture of users' acceptance of these technologies. In other words, the acceptance of being a cyborg is still under investigation as the technology itself is under development (Reinares-Lara et al., 2018). While, this research aims to investigate the acceptance of cyborg as an entity in society, which is still under development as a technology, and nothing is known yet about how humans will perceive cyborg individuals when they become a reality. To be precise, this research is investigating the acceptance of cyborg and robot services when compared with human services, especially in healthcare services, and by developing a model that can identify the choice criteria among these types of services. In the next sections, this research will review the related literature of robot, cyborg, and human services in the healthcare sector.

7.2 Literature Review

In general, healthcare services are intangible and can't be measured, unlike physical products. Consequently, the interaction between consumers and the employees of the service institutions are representing one of the core tools in evaluating the service quality (McLaughlin & Kaluzny, 2006; Mosadeghrad, 2013). Furthermore, the employee characteristics (e.g. empathy) should be taken into consideration during the hiring process, as they have a major influence on the consumers' perception of value associated with the offered service (Namasivayam & Denizci, 2006). In this context, empathy isn't a personal trait as much as it is a skill that can be created and developed to enhance consumer-employee interaction, which could lead to consumer satisfaction (Malle & Pearce, 2001). It is related to understand consumers' perspectives and interact with them emotionally (Davis, 1983). In the healthcare sector, patients' perception of the employees' empathy while interacting with them during the service encounter will impact positively their perception of the service quality (Purcarea et al., 2013). On the other hand, technology also has another important role in improving service quality and therapy performance in the healthcare sector (Calman et al., 2007). The technology could be considered very important in the healthcare sector when compared to other sectors. This means, healthcare organizations must acquire the new technologies and cope with using them through its service processes. It is a necessity and not an option, to ensure business continuity and to utilize competitive advantage for healthcare organizations. In addition, it also improves the level of the offered services to patients, and impacting positively their health and quality of life (Phichitchaisopa & Naenna, 2013).

In the healthcare sector, patients could use their emotions to continue or to end the service buying process. Their behavioral intention could be associated with the perception of arousal and pleasure, and the service rejection could be associated with the negative emotions (Ladhari & Rigaux-Bricmont, 2013; Ladhari et al., 2017). Some researches pointed to the impact of positive emotions on patient satisfaction. They claimed that it could be used as a strong determinant of patient’s choice among different healthcare institutions, either in public or private ones (Pinna, Chiappa, & Atzeni, 2018; Vinagre & Neves, 2010). Meanwhile, pleasure and arousal have a significant effect on the intention to choose between different service providers. These types of emotions should be stimulated by the direct interaction with the frontline employees and the perception of overall service quality (Lim, 2014). In the same context, these dimensions have a strong relation to service quality in healthcare services wherein a patients’ emotions are affected by the positive perception of healthcare service quality, consequently reflecting on the positive behavioral intention toward healthcare service providers. Furthermore, the perception of service quality and positive emotions could be a result of effective interaction with the employees, who are involved in the service delivery (Ladhari & Rigaux-Bricmont, 2013). In general, these kinds of emotions have a great influence on the intention and purchase decision and they could inhibit or motivate both of them (Pappas et al., 2013). As for the technology acceptance context, Olarte et al. (2017) and Pelegrín-Borondo et al. (2016) developed the CAN model to assess the acceptance of technological implants. The authors used positive and negative emotional dimensions. Whereas, some researchers are looking to the arousal and pleasure as the most appropriate determinants of human emotional state (Pelegrín-Borondo et al., 2015). These two dimensions had been introduced with the dominance emotional dimension (i.e. PAD emotional state model) by Mehrabian and

Russell (1974). Being the level of emotional pleasure and the level of emotional arousal are the most two emotional dimensions supported by the literature (Cohen et al., 2008; Pelegrín-Borondo et al., 2015; Russell, 1980, 2003). Accordingly, arousal and pleasure were found to be important in the attitudes toward robotic technology for both utilitarian and hedonic tasks (Kulviwat et al., 2007). Human emotional arousal and the expressed pleasure during the interaction with social robots could impact the acceptance significantly, either positively or negatively, and upon the human emotional state (Damholdt et al., 2015). Because of that, arousal and pleasure emotions could promote behavioral engagement, as in autism therapy using social robots (Rudovic et al., 2017). Pleasure and arousal could be consistent for different types of social robots. For example, the successful patient-robot interaction process could be stimulated by emotional pleasure and arousal. The perception of these emotions will be linked to the robot's ability to induce these emotions toward the patients and during the interaction process. Also, the robots' interactive features could enhance the users' emotional response, such as in elderly healthcare applications, where the elderly people's intentions toward social robots are strongly correlated with their perception of arousal and pleasure emotions. This also applies to pharmaceutical drug delivery tasks. A robot's positive emotional response toward patients can lead to stimulating patients' acceptance of robot technologies (Zhang et al., 2010, 2009).

Studying the factors affecting the acceptance of the new technologies in the healthcare sector is essential to guarantee success in the utilization process of these technologies (Lai, 2014). Different studies have been investigating the acceptance of new technologies in healthcare services by applying technology acceptance models and theories, which have been explained in the previous chapters, such as the original Technology Acceptance Model (TAM) for Davis (1989) and its extensions, the Theory of Planned Behavior (TPB) for Ajzen (1991), the Theory of Reasoned Action for Fishbein and Ajzen (1975), the Unified Theory of Acceptance and Use of Technology (UTAUT1) for Venkatesh et al. (2003) and UTAUT2 for Venkatesh et al. (2012). For instance, the acceptance of electronic health systems (e-health), mobile health services (m-health), and health information systems have been investigated by using the aforementioned technology acceptance models. Some studies observed that Effort Expectancy (EE) is the dominant influencer on the acceptance of these technologies, through its direct impact (Aggelidis & Chatzoglou, 2009; Keikhosrokiani, Mustaffa, Zakaria, & Baharudin, 2018; Pai & Huang, 2011) or through its impact on Performance Expectancy (PE) and attitude dimensions (Chow et al., 2013). However, literature is supporting the PE as the most significant determinant of the intention toward these technologies when compared to EE (Alsharo et al., 2018; Chang, Pang, Tarn, Liu, & Yen, 2015; Chen et al., 2013; Dünnebeil, Sunyaev, Blohm, Leimeister, & Krcmar, 2012; Hendrikx et al., 2013; Kijsanayotin et al., 2009; Lai, 2014; Phichitchaisopa & Naenna, 2013; Sezgin, Özkan-Yildirim, & Yildirim, 2017; Sun et al., 2013; Dhanar, Reza, Meyliana, Widjaja, & Hidayanto, 2017) and the social influence as well (Bawack & Kamdjoug, 2018; Chu et al., 2018; Guo et al., 2012; Hossain, Quaresma, & Rahman, 2019; Lee & Rho, 2013). But it is important to mention that, the situation regarding the technology acceptance determinants could be changed and based on the type and the use of any technology. That would imply the emergence of new utilizations of technologies and could consequently create new rankings in the level of technology acceptance dimensions or even create a need to integrate new dimensions while studying such technologies. For example, empathy showed a positive influence on human expectations towards the robot's behavior and on stimulating a successful interaction with it in the service settings (Niculescu et al., 2013). Likewise, some researches in the literature refer to empathy as a component of robot social abilities. They considered it a significant influencer on the intention to use social robots, and they integrated it within the technology acceptance models while investigating the social robot's acceptance (e.g. Heerink et al., 2010b, 2010a; Smarr, 2013). Also, the perceived risk is associated with the uncertain situations, such as in online transactions, where it has been integrated into the technology acceptance models to investigate such context, and it has been found as an important predictor of the intention to use these technologies (e.g. Moqbel & Bartelt, 2015; Özbek, Gunalan, Koc, Şahin, & Kas, 2015; Pavlou, 2003; Shaikh, Glavee-Geo, & Karjaluoto, 2018; Wu & Ke, 2015). Furthermore, it has been used in studying the acceptance of wearable technologies for healthcare applications (e.g. Li, Wu, Gao, & Shi, 2016; Nasir & Yurder, 2015; Yang, Yu, Zo, & Choi, 2016) and in the electronic exchange of information across healthcare sector too (e.g. Ahadzadeh, Sharif, Ong, & Khong, 2015; Chu et al., 2018; Hsieh, 2014). Some authors pointed to the importance of the perceived risk in human-robot interaction. From their perspective, once consumers recognize that the risk is more than the benefits, they may avoid the use of robots at all (Hancock et al., 2011). However, the risk impact has been assessed through other dimensions (e.g. trust and social-robot characteristics). But the need is to investigate the impact of this construct by itself and through extending the conceptual models to include the perceived risk in assessing the acceptance of robotic technology (Blut et al., 2018), since the previous studies pointed to risk as an outcome (or side effect) of using such technologies, not as users perception and without integrating it into their research models (e.g. Destephe et al., 2015; Lilley, 2013; Matsui et al., 2018; Wirtz et al., 2018; Young et al., 2009), such as in healthcare applications (e.g. Kates et al., 2015; McColl et al., 2013; Moro, 2018; Young et al., 2009).

Concerning robot acceptance in the healthcare sector, technology acceptance models have been used to assess the acceptance and diffusion of this technology across this sector. For instance, Alaiad et al. (2013) used the UTAUT model and found the PE followed by the social influence and the facilitating conditions as the most significant predictors of the intention to use healthcare robots. They pointed to the usefulness of these robots in terms of daily life improvement, quick treatment, and fast recovery. Once patients perceived these benefits, they would be more willing to adopt such technologies. Then, Alaiad and Zhou (2014) extended the previous model with new variables (i.e. trust, ethical concerns, legal concerns, and privacy concerns) and tested it in the same context. The results pointed to the importance of PE, social influence, facilitating conditions, privacy concerns, trust, and ethical concerns in predicting the intention of the robot use. Whereas, social influence had the strongest impact on the intention to use and among the other variables.

On the other hand, a limited number of researches have been trying to investigate the robots acceptance when compared to humans in service settings. For instance, Stock and Merkle (2018) tried to compare consumer perceptions in case the frontline employee is a robot and in case the employee is a human during the service encounter. The results showed no differences in consumer responses in both cases. Merkle (2019) also performed the same experiment and compared the consumer satisfaction when a robot is a frontline employee and when a human is the frontline employee. The same satisfaction level for both employees (i.e. robot and human) was obtained for the appropriate service conditions. However, satisfaction declined more for human employees in service failure conditions. The author referred these surprising results to the consumer expectations towards robot employees in terms of controllability and flexibility. They claimed that humans have more controllability and flexibility than robots. Therefore, consumers perceive the robot failure less than the human one. Even though, there is still a need to develop a conceptual model that can explain robot acceptance in service encounters and as an employee, who has the ability to interact with consumers, which represents one of the research objectives, especially in healthcare services.

Regarding cyborg technology, the term itself is immature and technology is still in the development stage, especially for human enhancement purposes. However, not much is known about its acceptance in society. However, the society has already accepted the use of this technology (e.g. technological and physical implants) for restoring physical functions, such as in Cochlear Implants (CI), and for increasing seductive capacities, such as in breast implants (Moser & Aiken, 2011; Pelegrín-Borondo, Reinares-Lara, et al., 2017). For instance, CI is seen as a hearing aid to help deaf people to restore their hearing ability. Whereas, it could be used as an enhancement to increase human hearing capacity to beyond the normality. Therefore, this shift in the use from therapy into enhancement could change people's perception of these technologies (Joseph Lee, 2016). In addition to that, some users of CI for therapy purposes are introducing themselves as cyborg entities (Christie & Bloustien, 2010). Also, Gao et al. (2015) studied the acceptance of healthcare wearable technologies. The authors pointed to three significant factors related to the intention to use wearable technologies in terms of privacy, healthcare, and technology perspectives. Their results suggested that the importance of these factors is depending on its application (i.e. medical or fitness). For example, social influence was significantly important for fitness wearables. However, PE was one of the important determinants of medical wearable technology acceptance. On the other side, the ethical issues related to the associated risk with these technologies and their limits are important topics that should be discussed. The successes of cyborg technologies will depend on the offered benefits and people’s perception of these benefits (Schicktanz et al., 2015). Ethically, technological implants for therapy use are accepted. While, it is still unclear for enhancement applications, despite that some authors mentioned the critical need for reformulating the meaning of ethics in terms of moral judgments, to be applicable on this type of technology (Schermer, 2009). Reinares-Lara et al. (2018) studied the effect of ethics on the acceptance of technological implants. The authors mentioned the ethical problem, which is covering different areas, such as personal security and privacy, and its effect on personal identity. The study implemented the ethical construct into the CAN model for investigating its moderating influence on the acceptance of brain implants for increasing capacities. The model consisted of PE, EE, emotional dimensions (i.e. negative emotions, positive emotions, and anxiety) and social influence as the determinants of the intention to use technological implants. Even though results didn’t prove the moderating effect of the ethical side on the implants' acceptance, it explained the intention differences in using them. Meanwhile, the same results confirmed the impact of PE, EE, negative emotions, positive emotions, and social influence on the intention to use, where the last two constructs had the strongest impact. This is consistent with the results of the Pelegrín-Borondo et al. (2017) study. The same results also have been confirmed by Pelegrín-Borondo et al. (2016) study when the intended recipients of the implant are oneself, not their children. Because when the decision is related to their children, the only predictors of the intention and use behavior was the positive emotions, negative emotions and the social influence. Consequently, studying the acceptance of cyborg technology should consider the cultural differences during the investigations. For instance, CAN model with the integration of the ethical side, should be investigated in different countries to be able to generalize the results, as ethical aspects are inherently cultural (Reinares-Lara et al., 2018). After all, these studies have been investigating the acceptance of being a cyborg. While, one of this research objectives is to study the acceptance of cyborg as an entity in the healthcare service encounter and when compared to services offered by robots and humans. And since cyborg represents a combination between technology and humanity, the factors applied on robot and human services will be applied on the cyborg, in order to investigate its acceptance form patents' perspectives and in the healthcare service encounter.

Chapter 8: Measurement Scale

8.1 Introduction

A quantitative methodology was used in this research. In addition to that, the measurement scale was developed based on the literature review using the 11-point scale (0 to 10). Also, the questionnaire survey was conducted online, and the data were collected from Jordanian students in different universities.

The partial least-square structural equation modeling (PLS-SEM) technique was used to examine this research model. This technique utilizes a component-based approach and gives a simultaneous examination of the measurement model and the structural model. Furthermore, it is a suitable technique to handle various relationships at the same time, doesn't need a normal distribution, and is recommended for investigating complex frameworks. More information about PLS-SEM will be discussed in Chapter 9. In the following sections, this research developed the measurement scale for each construct based on the literature review.

8.2 Effort Expectancy and Performance Expectancy:

Venkatesh et al. (2003) introduced EE and PE in the Unified Theory of Acceptance and Use of Technology (UTAUT) and adopted the measurement scales that had been used by Technology Acceptance Model (TAM1) for Davis (1989) and by TAM2 for Venkatesh and Davis (2000). Later on, Venkatesh et al. (2012) extended the UTAUT model to introduce UTAUT2 and they used the same scale adopted by Venkatesh et al. (2003). This measurement scale has been used in investigating the acceptance of technology in different applications (e.g. Bawack & Kamdjoug, 2018; Chen, Chang, & Chen, 2017a; Chu et al., 2018; Dünnebeil et al., 2012; Guo et al., 2012; Kijsanayotin et al., 2009). Hence, the development of this research measurement scale was based on previous researches in healthcare and robotic context (e.g. Alaiad & Zhou, 2013, 2014; Alaiad et al., 2013; Graaf, Allouch, & van Dijk, 2019; Hossain et al., 2019; Lu, Papagiannidis, & Alamanos, 2019; Ortega et al., 2016; Phichitchaisopa & Naenna, 2013; Rho et al., 2014; Saigí-Rubió et al., 2014; Talukder, Chiong, Bao, & Malik, 2019; Venkatesh et al., 2012; Wagner, Nimmermann, & Schramm-klein, 2019), to be consistent and convenient with investigating the acceptance and choice among robot, cyborg and human services. The scale items are shown in Table 8.1 for EE and in Table 8.2 for PE, and both were adopted form the measurement scale developed by Venkatesh et al. (2012).

Table 8.1 Effort Expectancy Scale Items

Robot	Cyborg	Human
REE1: Learning to relate with **Robot** will be easy for me	**CEE1:** Learning to relate with **Cyborg** will be easy for me	**HEE1**: Learning to relate with **Human** will be easy for me
REE2: My interaction with **Robot** will be clear and understandable.	**CEE2:** My interaction with **Cyborg** will be clear and understandable.	**HEE2:** My interaction with **Human** will be clear and understandable.
REE3: For me, interacting with **Robot** will be easy.	**CEE3:** For me, interacting with **Cyborg** will be easy.	**HEE3:** For me, interacting with **Human** will be easy.
REE4: It will be easy for me to be good at interacting with the **Robot**.	**CEE4:** It will be easy for me to be good at interacting with the **Cyborg**.	**HEE4:** It will be easy for me to be good at interacting with the **Human**.

REE: Robot Effort Expectancy, CEE: Cyborg Effort Expectancy, HEE: Human Effort Expectancy

Table 8.2 Performance Expectancy Scale Items

Robot	Cyborg	Human
RPE1: I will find the services offered by **Robot** useful.	**CPE1:** I will find the services offered by **Cyborg** useful.	**HPE1:** I will find the services offered by **Human** useful.
RPE2: The services offered by **Robot** will increase my chances of achieving things that are important to me.	**CPE2:** The services offered by **Cyborg** will increase my chances of achieving things that are important to me.	**HPE2:** The services offered by **Human** will increase my chances of achieving things that are important to me.
RPE3: Using Services offered by **Robot** help me accomplish things more quickly.	**CPE3:** Using Services offered by **Cyborg** help me accomplish things more quickly.	**HPE3:** Using Services offered by **Human** help me accomplish things more quickly.
RPE4: The use of services offered by **Robot** will let me a more efficient use of my resources (time, money, etc.).	**CPE4:** The use of services offered by **Cyborg** will let me a more efficient use of my resources (time, money, etc.).	**HPE4:** The use of services offered by **Human** will let me a more efficient use of my resources (time, money, etc.).

***RPE**: Robot Performance Expectancy, **CPE**: Cyborg Performance Expectancy, **HPE**: Human Performance Expectancy.*

8.3 Social Influence

The Social Influence (SI) showed a significant impact on the acceptance of new technologies and has been integrated into both versions of the Unified Theory of Acceptance and Use of Technology (UTAUT1&2) for Venkatesh et al. (2003) and Venkatesh et al. (2012). In addition to its important impact on the acceptance of different types of human services, such as in healthcare, retailing, banking and education sectors, in terms of influence and recommendations from friends, family, and relatives (e.g. Cagnina, 2016; Ejaz et al., 2014; Mazzarol & Soutar, 2002; Mokhlis, 2009). This research used the measurement scale adopted by the UTAUT2 model for Venkatesh et al. (2012) in measuring the SI construct (Table 8.3). Which has been used intensively and validated for studying the acceptance of different technologies, including robots and cyborg, and for different service settings, such as in the healthcare sector (e.g. Alaiad & Zhou, 2014; Alaiad et al., 2013; Gao & Bai, 2014; Gao et al., 2015; Hossain et al., 2019; Jang et al., 2016; Pelegrin-Borondo et al., 2017; Reinares-Lara et al., 2018; Talukder et al., 2019).

Table 8.3 Social Influence Scale Items

Robot Service	Cyborg Services	Human Service
RSI1: People who influence my behavior think that I should use service offered by **Robot**.	**CSI1**: People who influence my behavior think that I should use service offered by **Cyborg**.	**HSI1**: People who influence my behavior think that I should use service offered by **Human**.
RSI2: People who are important to me think that I should use service offered by **Robot**.	**CSI2**: People who are important to me think that I should use service offered by **Cyborg**.	**HSI1**: People who are important to me think that I should use service offered by **Human**.
RSI3: People whose opinions that I value, prefer that I should use service offered by **Robot**.	**CSI3**: People whose opinions that I value, prefer that I should use service offered by **Cyborg**.	**HSI1**: People whose opinions that I value, prefer that I should use service offered by **Human**.

***RSI**: Robot Social Influence, **CSI**: Cyborg Social Influence, **HSI**: Human Social Influence.*

8.4 Emotions (Pleasure and Arousal)

Mehrabian and Russell (1974) and Russell and Mehrabian (1977) suggested that what a person is feeling can be measured by employing a limited number of emotional dimensions. They proposed a scale with three dimensions: pleasure, arousal, and dominance (PAD). Eroglu et al., (2001) consider that "in many instances, the dominance dimension isn't included, probably due to Russell's (1979) recommendation that the pleasure and arousal alone represent the range of emotion exhibited in response to environmental stimuli" (p.181). Furthermore, there is a certain consensus that the arousal and pleasure emotional dimensions are the most appropriate dimensions to analyze the emotional response of an individual to a stimulus (Pelegrín-Borondo et al., 2015). In this context, different research studies have been using the measurement scale developed by Mehrabian and Russell (1974). For instance, the scale has been adopted by various researches in services sectors, such as in healthcare, tourism, and banking (e.g. Allard et al., 2009; Fang, Wu, Lee, & Liu, 2012; Pelegrín-Borondo et al., 2015). Also, in some of technology acceptance studies (e.g. Kulviwat et al., 2007; Msaed, Al-Kwifi, & Ahmed, 2017; Nasco, Kulviwat, Kumar, & Bruner, 2008) and online services context (e.g. Kim & Johnson, 2016; Mazaheri et al., 2014; Ruiz-Mafe, Chatzipanagiotou, & Curras-Perez, 2018). Meanwhile, PAD scale might be successfully reduced in some research studies for different context and applications and has also gained scale reliability (e.g. Ainsworth & Ballantine, 2014; Blasco-Arcas, Hernandez-Ortega, & Jimenez-Martinez, 2016; Chen, Chang, & Chen, 2017b; Das, 2013; Koo & Ju, 2010; Mazaheri, Richard, & Laroche, 2011; Mazaheri et al., 2014; Mummalaneni, 2005; Pelegrín-Borondo, Arias-Oliva, & Olarte-Pascual, 2017). Therefore, this research used the scale of Loureiro (2015), which was developed by Mazaheri et al. (2011) as a measurement scale of the arousal and pleasure emotional dimensions

(Table 8.4), and considering that this research is going to study future services, which will be offered by robot and cyborg in addition to human services.

Table 8.4 Emotions (Pleasure and Arousal) Scale Items

Emotions	Robot Service	Cyborg Services	Human Service
Pleasure	When I think of the service being provided by a **Robot,** I feel: **RP1**: Unhappy – Happy **RP2**: Annoyed – Pleased	When I think of the service being provided by a **Cyborg**, I feel: **CP1:** Unhappy – Happy **CP2:** Annoyed – Pleased	When I think of the service being provided by a **Human,** I feel: **HP1:** Unhappy – Happy **HP2:** Annoyed – Pleased
Arousal	When I think of the service being provided by a **Robot,** I feel **RA1**: Relaxed – Stimulated **RA2**: Calm – Excited	When I think of the service being provided by a **Cyborg,** I feel: **CA1:** Relaxed – Stimulated **CA2:** Calm – Excited	When I think of the service being provided by a **Human,** I feel **HA1:** Relaxed – Stimulated **HA2:** Calm – Excited

RP: *Robot Pleasure,* ***CP***: *Cyborg Pleasure,* ***HP***: *Human Pleasure,* ***RA***: *Robot Arousal,* ***CA***: *Cyborg Arousal,* ***HA***: *Human Arousal.*

8.5 Empathy

The measurement scale for empathy was adopted from Homburg and Merkle (2019), who studied the attitude towards the humanoid robot and developed the measurement scale for this construct based on Davis (1983), Hogan et al. (1984), and Parasuraman et al. (1991) studies. The scale items are shown in Table 8.5.

Table 8.5 Empathy Scale Items

Robot Service	Cyborg Services	Human Service
In my opinion, **Robot** is typically able to: **RE1**: Have a high level of empathy with respect to my needs as a consumer. **RE2**: Have no difficulty determine my needs. **RE3**: trying to determine my needs by adopting my perspective. **RE4**: Find it easy to adopt my perspective as a consumer. **RE5**: Adapt its interactions to my needs in different situations.	In my opinion, **Cyborg** is typically able to: **CE1**: Have a high level of empathy with respect to my needs as a consumer. **CE2**: Have no difficulty determine my needs. **CE3**: trying to determine my needs by adopting my perspective. **CE4**: Find it easy to adopt my perspective as a consumer. **CE5**: Adapt its interactions to my needs in different situations.	In my opinion, **Human** is typically able to: **HE1**: Have a high level of empathy with respect to my needs as a consumer. **HE2**: Have no difficulty determine my needs. **HE3**: trying to determine my needs by adopting my perspective. **HE4**: Find it easy to adopt my perspective as a consumer. **HE5**: Adapt its interactions to my needs in different situations.

RE: *Robot Empathy,* ***CE***: *Cyborg Empathy,* ***HE***: *Human Empathy.*

8.6 Perceived Risk

The items measuring the perceived risk (Table 8.6) were developed based on the scale adopted by Faqih (2016), which was originally developed by Shim et al. (2001) and has been used in different research studies in the literature (e.g. Alam & Yasin, 2010; EL-Masry, 2007; Pelegrin-Borondo et al., 2017; Yang, Pang, Liu, Yen, & Tarn, 2015).

Table 8.6 Perceived Risk Scale Items

Perceived Risk		
Robot	**Cyborg**	**Human**
RPR1: The services offered by **Robot** are risky	**CPR1**: The services offered by **Cyborg** are risky	**HPR1**: The services offered by **Human** are risky
RPR2: There is too much uncertainty associated with the services offered by **Robot**	**CPR2:** There is too much uncertainty associated with the services offered by **Cyborg**	**HPR2:** There is too much uncertainty associated with the services offered by **Human.**
RPR3: Compared with other methods of service, the services offered by **Robot** is riskier.	**CPR3:** Compared with other methods of service, the services offered by **Cyborg** is riskier.	**HPR3:** Compared with other methods of service, the services offered by **Human** is riskier.

***RPR**: Robot Perceived Risk, **CPR**: Cyborg Perceived Risk, **HPR**: Human Perceived Risk.*

8.7 Behavioral Intention to Use

Behavioral intention construct, which was introduced and defined by Fishbein and Ajzen (1975) as "an individual's subjective probability that he will perform some behavior" (p.288), has been used later on in the technology acceptance models, such as in TAM versions (Davis, 1989; Venkatesh & Bala, 2008; Venkatesh & Davis, 2000), UTAUT versions (Venkatesh et al., 2003, 2012) and CAN model (Pelegrín-Borondo et al., 2016). Venkatesh and Davis (2000) measurement scale was adopted for measuring the intention to use construct since it has been used and validated in different previous studies while investigating the acceptance of the new technologies, including robots and cyborg, and for different service settings (e.g. Chen et al., 2017; Pelegrín-Borondo, Reinares-Lara, et al., 2017; Reinares-Lara et al., 2018; Weng, 2016). Furthermore, the same scale was used for human services, to maintain the consistency of the construct's items (Table 8.7). Even though, some studies about services that are operated and offered by humans have used the same scale to measure behavioral intention (e.g. Chow et al., 2013; Im et al., 2007; Heijden, 2004; Wu, Li, & Fu, 2011).

Table 8.7 Intention to Use Scale Items

Robot Service	Cyborg Services	Human Service
RIU1: I will try to use services offered by **Robot.**	**CIU1:** I will try to use services offered by **Cyborg.**	**HIU1:** I will try to use services offered by **Human.**
RIU2: I predict that I will use services offered by **Robot**	**CIU2:** I predict that I will use services offered by **Cyborg.**	**HIU2:** I predict that I will use services offered by **Human**.

***RIU**: Robot Intention to Use, **CIU**: Cyborg Intention to Use, **HIU**: Human Intention to Use.*

Chapter 9: Data Collection Procedures and Analysis Process

9.1 Data collection procedures

An online survey was developed using google forms to test the research hypotheses. The data had been collected among students in different Jordanian universities between May and September 2019. Several visits had been conducted to the universities in different times and locations (e.g. Cafeterias, Libraries, and Classes) to reach the acceptable number of valid surveys. The participants were requested to answer the online survey questions after inviting them in person through universities professors, employees, and friends. The survey hyperlink had been sent to the participants via email, Facebook messenger, and WhatsApp. And the participants used their smartphones, laptops, or tablets to answer the survey questions.

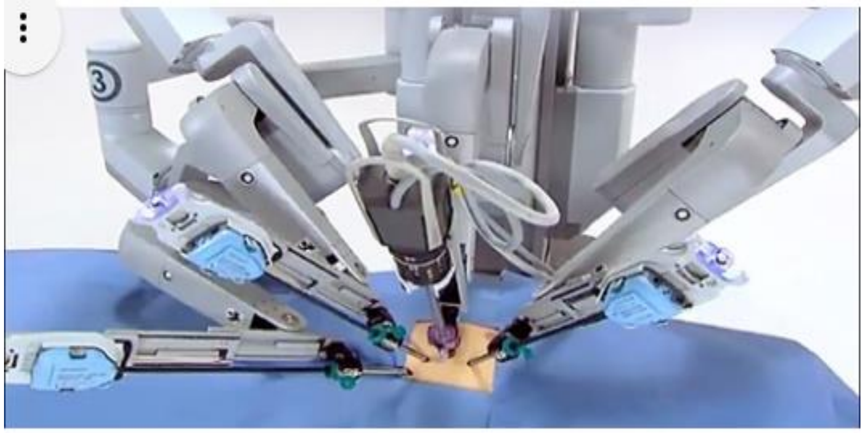
Since the Jordanian population are native Arabic speakers, the survey was translated into Arabic. The translation process involved two steps. The first one was to match the instruments developed by this research (Chapter 8) with the Arabic versions used by Arabian researchers. (e.g. AbuShanab & Pearson, 2007; AbuShanab, Pearson, & Setterstrom, 2010; Adwan, Al-Adwan, & Smedley, 2013; Faqih, 2011; Masoud, 2013). The second step was to review the translated questions by an Arabic language expert to ensure the correct phrasing and structure of the survey questions. The translated version had a different hyperlink than the English version, and both links were sent to the participants, which gave the participants the freedom to choose among those two versions.

Based on the assumption that the Jordanian students were unfamiliar with this kind of technology, an explanation about cyborg and robot technologies was used as an introduction to the online survey. Which is shown below:

"*A cyborg is a human with technological devices implanted in their body to improve their capacities over their innate ones (for example, improved memory, speed of calculation, or physical abilities). A robot is a programmable machine capable of performing certain operations autonomously and replacing humans in some tasks. What do you think about a surgery being undertaken by a human, a cyborg, or a robot? We are conducting a study about the choice between a human doctor, a cyborg doctor, and a robot for medical services. For instance, think about a surgery to correct a deficiency in one of your eyes*".

In addition to that, a press release about the use of robots in surgeries with an illustrative photo had been placed after the introduction, to give the participant a general idea about the current attempt to use autonomous robots in medical surgeries. "*According to recent news published in Newsweek magazine, the Smart Tissue Autonomous Robot (STAR), a robot to do surgery, has been proved a more precise than expert human surgeons performing the same tasks*".

Figure 9.1 STAR Robot



Source: (Bushak, 2016)

After the introduction, the survey was requesting participants gently to start answering the survey questions. Section one-part one, which was used to measure the proposed robot services, was introduced with the following paragraph: "*Consider that a Robot doctor could do a surgery to correct a deficiency in one of your eyes. Indicate the extent to which you agree or disagree with the following statements on a scale of 0 (strongly disagree) to 10 (strongly agree), 5 being neither agree nor disagree*". It had 21 questions to measure the intention to use, effort expectancy, performance expectancy, social influence, perceived risk, and empathy. The items were measured on 11-points Likert scales (0=Strongly Disagree, 10=strongly Agree). Section one-part two introduced by: "*On a scale of 0 to 10, indicate the extent to which the following descriptions reflect your feeling about using Robot Services. For example, in the first item, 0 would mean you feel unhappy with Robot services, and 10 would mean you feel Happy: When I think of the service being provided by a Robot, I feel:*". It contained 4 questions to measure emotions (Pleasure and Arousal) using 11-points Likert scales ("Unhappy=0, Happy=10", "Annoyed=0, Pleased=10", "Relaxed=0, Stimulated=10", and "Calm=0, Excited=10").

The measurement scale of the proposed cyborg services had been created under section two-part one and section two-part two. Like the previous section, the questions initiated with the following explanation: "*Consider that a Cyborg doctor could do a surgery to correct a deficiency in one of your eyes. Indicate the extent to which you agree or disagree with the following statements on a scale of 0 (strongly disagree) to 10 (strongly agree), 5 being neither agree nor disagree:*". And part two started with: "*On a scale of 0 to 10, indicate the extent to which the following descriptions reflect your feeling about using Cyborg Services. For example, in the first item, 0 would mean you feel unhappy with Cyborg services, and 10 would mean you feel happy: When I think of the service being provided by a Cyborg, I feel:*". The question structure was the same as the previous section. Only the word Robot was replaced by Cyborg.

In section three, the questions had been reconstructed to represent human services. Part one started with: "*Consider that a Human doctor could do a surgery to correct a deficiency in one of your eyes. Indicate the extent to which you agree or disagree with the following statements on a scale of 0 (strongly disagree) to 10 (strongly agree), 5 being neither agree nor disagree*:". And part two started with:" *On a scale of 0 to 10, indicate the extent to which the following descriptions reflect your feeling about using human services. For example, in the first item, 0 would mean you feel unhappy with human services, and 10 would mean you feel happy: When I think of the service being provided by a human, I feel:*".

After finishing the above-mentioned 75 questions, the participants were asked to answer a few general questions. The first question was used to understand the participants' preferences among the three surgeons (i.e. robot, cyborg, and human). A multiple-choice question with three options had been used. The participant had the ability to choose one option (A Human doctor, A Cyborg doctor, or A Robot doctor). The second question was an open question that gave the participants the space to explain the advantages they considered in their choice in the first part. In addition to the disadvantages, which represented by answering the second part. In the third question, the participants were asked to choose the second option they may accept to carry out the proposed surgery to correct a deficiency in one of their eyes (A Human doctor, A Cyborg doctor, or A Robot doctor). Finally, the survey requested the participants to choose their gender, age interval, level of study, the field of study, country, and their universities/institution name.

9.2 Data Analysis Process

9.2.1 Introduction

The Structural Equation Modeling (SEM) has been spread widely in recent years, especially in social science studies (Roldán & Sánchez-Franco, 2012). Two methods are associated with SEM, Covariance-Based SEM (CB-SEM), and Partial Least Squares SEM (PLS-SEM). In general, CB-SEM is preferably used in confirmatory researches, where the purpose of such researches is to confirm or reject the theories. These theories are represented by a set of variables that have a systematic relationship and could be tested empirically. However, the PLS-SEM is more likely to be used in the exploratory analysis (i.e. predictive applications and building theories), by assessing the theoretical models to explain the variance of the dependent variable (Hair, Hult, Ringle, & Sarstedt, 2017). Originally, PLS-SEM had been developed by Wold (1975) under the name of Nonlinear Iterative Partial Least Squares (NIPALS) and was extended by Lohmoller (1988). As per Hair, Sarstedt, Ringle, and Mena (2012), PLS-SEM was developed to represent an alternative method to the CB-SEM. Furthermore, PLS-SEM assesses the model relationships in a series of ordinary least squares (OLS) regressions, in order to maximize the explained variance of the endogenous latent variables. The sequence of OLS regressions makes PLS-SEM achieve a higher level of statistical power and lower demand concerning the sample size. In contrast, CB-SEM is reproducing an empirically observed covariance matrix by estimating the model parameters. However, it preferred not to deal with small sample sizes to avoid incorrect and non-convergent solutions. Therefore, PLS-SEM could be the best choice if the research is intended to identify the relationship between the latent variables or to predict them in the research model (Reinartz, Haenlein, & Henseler, 2009).

In the CB-SEM method, as the number of indicators increases for each construct, it will lead to greater reliability, accurate estimation for the parameters, and better solutions. But up to a certain point, further indicators will lead to the excessive power of the goodness-of-fit tests (MacCallum, ABrowne, & ASugawara, 1996). Regarding the sample size, more than 200 samples size could be considered as a rule of thumb. Because as the sample size gets bigger, the standard error of model estimates will decrease. The sample size is important for the CB-SEM to ensure model identification, since the sample covariance matrix S should be positive-definite, which will not be guaranteed unless the sample size exceeds the number of indicators (Reinartz et al., 2009; Scott, 1983).

PLS-SME deals with block variables, rather than CB-SEM which deals with latent variables. These block variables represent the weighted average of the construct indicators which can result in measurement error. In fact, for a specific number of indicators, any increase in sample size will not lead to unbiased estimates. And for a specific sample size, the increase in indicators will decrease partially the parameter estimates. Actually, PLS-SME could be used as an alternative to the CB-SEM when the later reaches its limit, such as when the sample is small or the indicators per construct become too large (Reinartz et al., 2009).

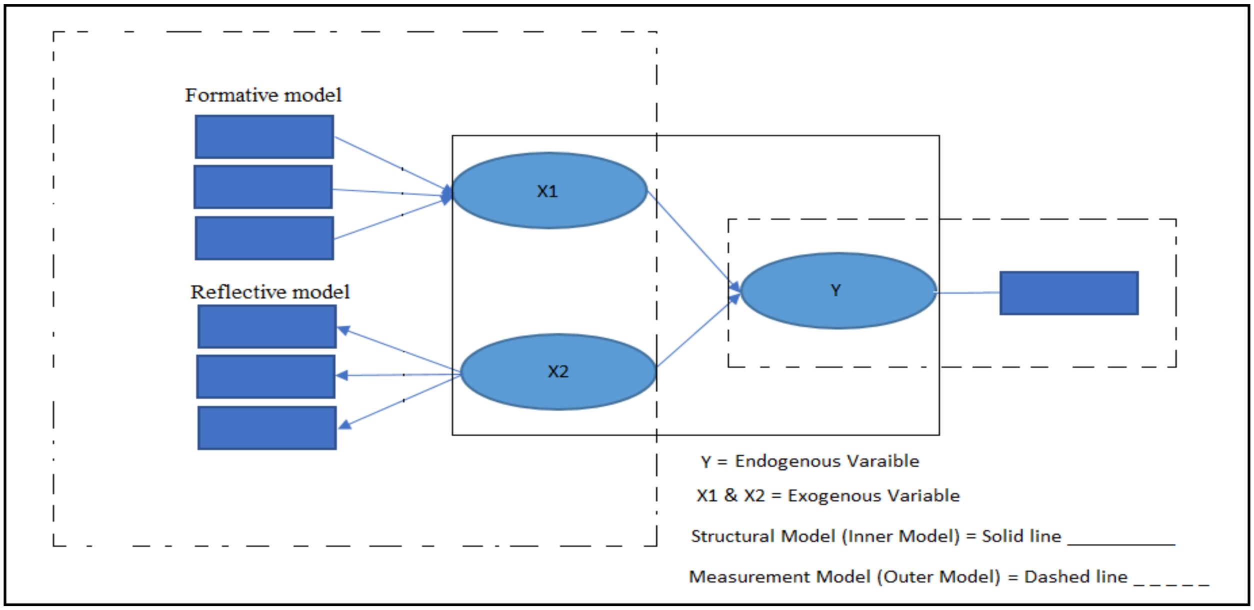
In general, the CB-SEM is based on the common factor model, which is calculating the covariance between variables to find a solution and the analysis is using only the common variance. Furthermore, before the assessment of the theoretical model, the specific and the error variance are removed. Normally, the specific variance is used to predict the dependent variable in the theoretical model. And removing it from the theoretical model examination represents one of the CB-SEM method limitations. In contrast, PLS-SME is based on the composite model which is using all the variance of the independent variables to predict the dependent variable. In fact, the choice among these two methods will depend on the nature of the research and its objectives. In this context, the following criteria could be applicable while choosing among the two methods (Garson, 2016):

1. Select PLS-SEM if the main objective is to predict or identify the key constructs.
2. Select PLS-SEM if the main objective is to extend an existing theory or if the research is exploratory.
3. Select the CB-SEM if the main objective is to test a theory, confirm a theory, or compare alternative theories.

Since the goal of doing this research was to predict the consumer intention to use cyborg, robot, and human services, in addition to identifying the key drivers that explain consumer choice criteria, this research used the PLS-SEM method to test the proposed hypotheses using SmartPLS 3 software. Furthermore, the same method has been recommended to be used for exploratory purposes, as explained above (Hair, Matthews, Matthews, & Sarstedt, 2017; Reinartz et al., 2009).

Technically speaking, SEM consists of two main elements, measurement model and structural model. The measurement model, which called also outer model, is representing the relationship between model variables and their indicators. However, the structural model is representing the structural path between model variables, and it is called the inner model too. The variables could be exogenous (i.e. independent variables) or endogenous (i.e. dependent variable). Furthermore, the indicators could be formative or reflective. In case the variable will be measured by using a formative indicator, the arrow will point into the variable in the outer model. On the contrary, if the arrow points into the indicators, the variable will be measured using reflective indicators. Figure 9.2 is an example of theoretical SEM and constructs (Hair, Matthews, et al., 2017).

Figure 9.2 Theoretical SEM & Constructs



Source: (Hair, Matthews, et al., 2017)

9.2.2 Measurement Model Evaluation

The assessment process of the research hypothesis starts by assessing the measurement model through three assessments. Calculating the Cronbach alpha and composite reliability is the first step for evaluating the internal consistency reliability of the reflective measurement model. The composite reliability has been recommended over the Cronbach alpha since it considers the different weights of the indicators, rather than Cronbach alpha, which equal the indicator loadings (Dijkstra & Henseler, 2015). Both values should be more than 0.70 to confirm the adequate reliability of the constructs (Hair, Ringle, & Sarstedt, 2013). The second assessment is to evaluate the convergent validity of the indicators by determining the Average Variance Extracted (AVE) for each construct, which is calculated based on examining the outer loading of each indicator. The value of the AVE should be higher than or equal to 0.50 to confirm convergent validity (Hair et al., 2013). Finally, discriminant validity is the third assessment for the measurement model, to confirm that the construct indicators are able to measure their construct, not the other constructs. In other words, the construct measures should not be correlated with the measures of the other constructs. The evaluation of the discriminant validity can be achieved by determining the square root of AVE for the construct, which should be greater than the correlation with the other constructs (Roldán & Sánchez-Franco, 2012). The idea from this comparison is to confirm that the AVE of the construct is greater than the variance between the construct and other constructs, and as recommended by Fornell and Larcker (1981). Moreover, Henseler, Ringle, and Sarstedt (2015) recommendation were to divide the heterotrait correlations (i.e. the correlations of the indicators across constructs measuring different constructs) by the monotrait correlations (i.e. the correlations of the construct indicators) to get the Heterotrait-Monotrait Ratio (HTMT), which its value should be less than 0.9 to confirm the discriminant validity (Gold, Malhotra, & Segars, 2001; Hair, Matthews, et al., 2017; Henseler et al., 2015).

9.2.3 Structural Model Evaluation

Since PLS doesn't assume the normal distribution of the data. This means it would not be possible to apply the parametric significance test to assess if coefficients are significant (e.g. path coefficients and outer loadings). Instead of that, PLS-SEM uses a bootstrap procedure to estimate the path coefficients. In bootstrap, a larger number of samples are produced from the original sample. This production involves a replacement. Which means, for each random observation production, the produced observation is returned to the original sample and before producing the next observation. Furthermore, each bootstrap sample should have the same number of observations as the original sample. The recommended number of bootstrap samples is 5000 (Hair, Hult, et al., 2017). Accordingly, the first step in assessing the structural model is to test the model hypotheses by evaluating the path coefficients between exogenous variables (i.e. independents variables) toward the endogenous variable (i.e. dependent variable). The values are approximately between -1 to +1. The negative value refers to the negative relationship between the two constructs and a positive value is an indication of a positive relationship. The closer the value to 1 (- or +), the stronger the relationship. Eventually, the standard error obtained from bootstrapping will show if the coefficient is significant or not by computing the t-value and p-value of the structural path coefficient. When the empirical t-value is greater than the reference value, the coefficient will be significant at a certain level. The significant level is obtained based on the p-value. The common references for the one-tailed tests are 1.28 at a 10% significance level, 1.65 at a 5% significance level, and 2.33 at a 1% significance level. And for the two-tailed tests, 1.65 at a 10% significance level, 1.96 at a 5% significance level, and 2.57 at a 1% significance level (Hair, Hult, et al., 2017).

The second test to evaluate the PLS model is the coefficient of determination (R^2) of the endogenous variable. This value shows the predictive power of the model and indicates the variance in the endogenous variable, which explained by the exogenous variables. In other words, it shows the effect of the exogenous variables on the endogenous variable (Chin, 2010; Roldán & Sánchez-Franco, 2012). The values 0.19, 0.33, and 0.67 of R^2 are considered weak, moderate, and substantial, respectively (Chin, 1998). In addition, the predictive relevance of the endogenous construct can be evaluated by applying the blindfolding procedure for a specified omission distance D with a value between 5 and 10, in order to obtain the Stone-Geisser's Q^2 value. The value of more than 0 is an indication of the predictive relevance of the endogenous variable. Negative value or value equal to 0 means the model is irrelevant to predict the endogenous variable (Geisser, 1974; Stone, 1974).

9.2.4 Partial Least Squares Multi-Group Analysis (PLS-MGA)

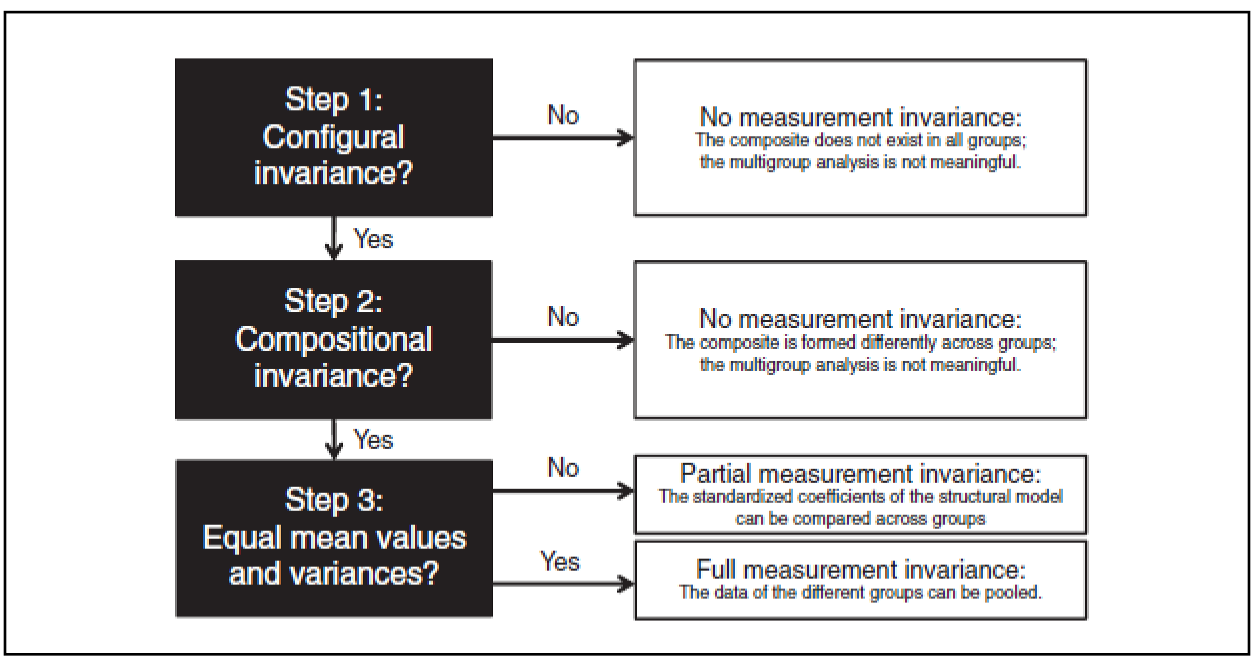
The idea from using the multigroup analysis is to test if there are significant differences among the pre-defined data groups in the estimates, such as outer loadings, outer weights, and path coefficient. This research aimed to compare the three models (i.e. robot, cyborg, and human services model) with each other. In fact, before applying the PLS-MGA, the measurement invariance of composite models (MICOM) analysis should be applied first, to avoid misleading, which could be a result of the multigroup analysis if the measurement invariance isn't confirmed. Three steps procedure was introduced by Henseler, Ringle, and Sarstedt (2016) for the MICOM and they are as follows:

1. **Configural invariance**: it involves a qualitative evaluation of the invariance in measurement indicators, data treatment, and algorithm settings/criteria.
2. **Compositional invariance**: in this step, the invariance in indicators weights should be achieved by comparing the original correlation with the correlation of 5%-quantile of the distribution. The original correlation should be equal to 1 or greater than a 5%-quantile correlation to confirm a compositional invariance.

3. **Equality of composite means and variances**: by using the pooled data, the PLS has to be applied to obtain constructs scores, to evaluate whether there is a difference between the mean and variance of the first model construct scores and the second model construct scores. The zero (or non-significant) difference means a full measurement invariance. Practically, the mean difference value and variance difference value should be within 2.5% and 97.5% boundaries (i.e. 95% confidence interval).

It is important to mention that, passing each step is a condition to proceed with the next one, especially for configural invariance and compositional invariance. This implies that, if the configural invariance is confirmed, compositional invariance could be evaluated. Otherwise, it isn't recommended to proceed with multigroup analysis at all. Meanwhile, if the compositional invariance is met, the equality of composite means and variances evaluation can be done. However, if the compositional invariance fails, the multigroup analysis would not be meaningful. Finally, if the quality of composite means and variances are met, full measurement invariance would be established. On the contrary, a partial measurement invariance would be the result, and we can proceed with the multi-group analysis. Figure 9.3 shows the MICOM procedure (Henseler et al., 2016).

Figure 9.3 MICOM Procedure



Source: (Henseler et al., 2016, pp.412)

Different methods have been introduced for the multigroup analysis within the PLS path modeling. For instance, the parametric approach, which was applied initially by Keil, Tan, Wei, Saarinen, and Wassenaar (2000), is based on estimating model parameters of each model separately and using the bootstrap to obtain standard errors that represent the input of the parametric test. However, some authors have doubts about the ability of this method to fit the PLS path modeling because it is based on assumptions about the distribution of the data, rather than PLS path modeling, which is considered as a distribution-free path modeling (Henseler, Ringle, & Sinkovics, 2009). Another parametric approach is called the Welch-Satterthwaite test, and it is used when two samples have unequal variances and/or have unequal sample sizes (Sarstedt, Henseler, & Ringle, 2011). Furthermore, Henseler et al.'s approach doesn't rely on distributional assumptions. It uses bootstrap analysis for each group, and their outcomes are used to evaluate group differences. This approach has been introduced by Henseler (2007) to resemble the parametric approach and it has been extended by Henseler et al. (2009). A fourth method is the permutation approach, which is used also in MICOM analysis. Same as the said approach, it fits the PLS path modeling, and it is considered as a distribution-free test. Additionally, this approach controls well for type 1 error and is more conservative when compared to parametric methods. Moreover, many researches have been recommended to use this approach (Hair, Sarstedt, Ringle, & Gudergan, 2017). Accordingly, this research will use the permutation approach to investigate the differences between research models in terms of independent variables impact on intention to use robot vs cyborg services, robot vs human services, and human vs cyborg services.

PART III: RESULTS

Chapter 10: Results

10.1 Descriptive Results

The data has been collected from 379 individuals from different universities in Jordan. 92% of the respondents are Jordanians and 8% were students from different Arabian countries, who are studying in the Jordanian universities. Based on the geographical area of the universities, 55.4% of the respondents were from the capital of Jordan (i.e. Amman) Universities, 21.4% from Al-Balqa Governorate universities, 10.6% from North of Jordan universities, 7.6% from South of Jordan universities, and 5% of the respondents were from East of Jordan universities. In terms of respondents' gender, 47% of the respondents were females, and 53% were males (Table 10.1).

Table 10.1 Gender

Gender	Frequency	Percentage
Male	201	53%
Female	178	47%

Also, 66% of the respondents were at the Bachelor level, 19% were studying Master, 9% at Associate degree (i.e. called in Jordan as Diploma, by studying two to three years in a college) studies and 6% were studying Ph.D. (Table 10.2).

Table 10.2 Level of study

Level	Frequency	Percentage
Associate degree	34	9%
Bachelor	250	66%
Master	73	19%
PhD	22	6%

This research classified the universities as public and private universities. 64.3% of the respondents were from public universities, and 35.7% in private universities (Table 10.3).

Table 10.3 Universities

Universities Classification	Frequency	Percentage
Public	244	64%
Private	135	36%

Regarding the field of study criterion, 26% engineering and computer sciences, 43.3% management and social sciences (e.g. business management, human resources, financial management, and languages), and 13% medical studies. Regarding age intervals, the majority of the respondents were 18-24 (50.7%) and the rest was distributed between 25-34 (24.3%), 35-44 (13.5%), 45-54 (7.9%), and +55 (3.6%) years' old intervals (Table 10.4).

Table 10.4 Age intervals

Interval	Frequency	Percentage
18-24	192	50.7%
25-34	92	24.3%
35-44	51	13.5%
45-54	30	7.9%
Over 55	14	3.6%

Before proceeding in measurement model assessment, structural model assessment, and comparative analysis for the three models, this research performed a one-way ANOVA t-test using Microsoft Excel analysis tool to check if there is a difference of respondents' preferences toward intention to use among the three options (i.e. human, cyborg, and robot services). The p-value of the ANOVA t-test showed a significant difference in the participants' intention to use among the three options (Table 10.5). In the same context, the survey contained two multiple-choice questions to get an idea about participants' preferences between proposed human, cyborg, and robot surgeons to perform a correction surgery of deficiency in one eye. The first question was: "Who would you prefer to carry out surgery to correct a deficiency in one of your eyes?" 258 out of 379 participants chose a human surgeon, which represents 68% of participants. 21% chose cyborg surgeon, and 11% preferred robot surgeons. The participants had been requested to mention the advantages and disadvantages of their choice. The second question was: "Who would you prefer as your second option to carry out surgery to correct a deficiency in one of your eyes?" 44% of participants chose cyborg surgeons, 32% chose human surgeons, and almost 24% decided to choose robot surgeons.

Table 10.5a One-way ANOVA T-test

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	1791.077	2	895.5383	100.78	5.18E-41	3.00366
Within Groups	10076.8	1134	8.886068			
Total	11867.88	1136				

Table 10.15b One-way ANOVA T-test Mean values

Groups	Count	Sum	Mean	Variance
Human Intention to Use	379	2888.5	7.621372032	6.378087
Robot Intention to Use	379	1735.5	4.579155673	11.06515
Cyborg Intention to Use	379	2166.5	5.716358839	9.21497

10.2 Robot Service Model

10.2.1 Measurement Model Assessment

The internal consistency reliability is the first criterion to be evaluated by using Cronbach's alpha and composite reliability, to confirm the adequate reliability of the constructs (Hair, Hult, et al., 2017). Hair et al. (2013) have suggested that Cronbach's alpha and composite reliability should be higher than 0.70. This research results confirmed the internal consistency reliability inasmuch as the values of Cronbach's alpha and the composite reliability for all constructs of the robot services measurement model were higher than 0.70. Furthermore, the standardized loading of the indicators should be greater than 0.70 and the t-value should be greater than 1.96 to ensure the correct reliability indicator in the measurement model. Even though, the values between 0.4 and 0.7 could be accepted if the t-value is above 1.96. Otherwise, any indicator values don't match the mentioned role of thumb should be eliminated (Hair et al., 2013; Pelegrín, González-Menorca, & Meraz, 2019). All the indicators of the robot services measurement model got standardized loading values greater than 0.70.

The positive correlation between the indicator and the alternative indicators of the same constructs means that the convergent validity is met. To obtain this, the Average Variance Extracted (AVE) value should be equal to or greater than 0.50 (Hair, Hult, et al., 2017). In this research, all constructs of the robot services measurement model had AVE values greater than 0.50, which confirmed the convergent validity of the measurement model. Table 10.6 shows loading values, Cronbach's alpha, Composite reliability, and AVE values.

The final step in assessing the measurement model is to measure the Discriminant validity, which is an indication that showing if the constructs indicators have the ability to measure their construct only, not the other constructs (Hair, Hult, et al., 2017). Two methods had been used to assess discriminant validity. The first one is the Fornell-Larcker criterion, which is comparing the correlation of the latent variable with the square root of the AVE values. To meet the discriminant validity, the square root of the AVE value for each construct should be greater than its correlation with the other constructs (Roldán & Sánchez-Franco, 2012). The second method is by assessing the Heterotrait-Monotrait ratio (HTMT) of the correlations. Which its value should be lower than 0.90 (Gold et al., 2001; Henseler et al., 2015; Teo, Srivastava, & Jiang, 2008). The robot services measurement model results confirmed the discriminant validity of the constructs indicators, where the HTMT values were less than 0.90 of all constructs, and the square root of AVE values for each construct was higher than the correlation value with the other constructs. Table 10.7 shows the HTMT, square root of the AVE, and correlation values for all

constructs.

Table 10.6 Internal Consistency Reliability & Convergent Validity for Robot Services Measurement Model

Variable	Indicators	Loading	Cronbach's alpha	Composite reliability	AVE
Arousal	**RA1**	0.945	0.875	0.941	0.889
	RA2	0.940			
Effort Expectancy	**REE1**	0.929	0.953	0.966	0.875
	REE2	0.934			
	REE3	0.939			
	REE4	0.940			
Empathy	**RE1**	0.849	0.936	0.952	0.798
	RE2	0.841			
	RE3	0.935			
	RE4	0.925			
	RE5	0.913			
Intention to Use	**RIU1**	0.963	0.926	0.964	0.931
	RIU2	0.966			
Pleasure	**RP1**	0.937	0.822	0.918	0.848
	RP2	0.904			
Perceived Risk	**RPR1**	0.893	0.873	0.917	0.786
	RPR2	0.823			
	RPR3	0.940			
Performance Expectancy	**RPE1**	0.942	0.941	0.957	0.849
	RPE2	0.925			
	RPE3	0.932			
	RPE4	0.886			
Social Influence	**RSI1**	0.932	0.926	0.953	0.871
	RSI2	0.944			
	RSI3	0.923			

RPE: Robot Performance Expectancy, REE: Robot Effort Expectancy, RSI: Robot Social Influence, RPR: Robot Perceived Risk, RE: Robot Empathy, RA: Robot Arousal, RP: Robot Pleasure, and RIU: Robot Intention to Use

Table 10.7 Discriminant validity of the Robot Services Measurement Model.

Variable	Arousal	Effort Expectancy	Empathy	Intention to use	Perceived Risk	Performance expectancy	Pleasure	Social Influence
Arousal	**0.943**	0.619	0.602	0.698	0.100	0.722	0.856	0.706
Effort Expectancy	0.566	**0.935**	0.711	0.795	0.049	0.777	0.614	0.774
Empathy	0.546	0.673	**0.893**	0.543	0.240	0.592	0.601	0.663
Intention to use	0.629	0.748	0.507	**0.965**	0.109	0.860	0.710	0.815
Perceived Risk	-0.098	0.040	0.229	-0.111	**0.887**	0.055	0.058	0.079
Performance expectancy	0.655	0.738	0.557	0.805	-0.002	**0.921**	0.721	0.881
Pleasure	0.728	0.548	0.533	0.625	-0.045	0.641	**0.921**	0.690
Social Influence	0.636	0.728	0.618	0.757	0.056	0.824	0.609	**0.933**

Note: values on the main diagonal are the square roots of the AVEs, below the diagonal: correlations between the constructs, and above the diagonal: HTMT values.

10.2.2 Structural Model Assessment

Before going further in the structural model assessment, a bootstrapping with 5000 sample size had been taken place to evaluate the path coefficient, R^2, and Q^2 values. Accordingly, the first step is to evaluate the path coefficient for all exogenous variables. All of these variables had values less or greater than 0. However, to consider the path coefficient as significant, the p-value should be less than 0.01, and the t-value should be equal or greater than 2.57 (Hair, Hult, et al., 2017; Roldán & Sánchez-Franco, 2012). According to this research results for the robot services: H1 (The influence of Effort Expectancy and Performance Expectancy), H2 (The influence of Social Influence), and H5 (The influence of perceived risk) were supported. However, H3 (The influence of Pleasure and Arousal) and H4 (The influence of Empathy) were rejected, since the path coefficient was not significant ($0.01 < p$ and $t < 2.57$).

The second criterion to evaluate the structural model was the coefficient of determination (R^2), which represents the variance explained by the exogenous variables of the endogenous variable (Chin, 2010). As a role of thumb, the values 0.67, 0.33, and 0.19 considered substantial, moderate, and weak, respectively. In general, the higher the R^2, the higher the predictive power of the model (Chin, 1998; Mosquera, Juaneda-Ayensa, Olarte-Pascual, & Pelegrín-Borondo, 2018). The value of R^2 was 0.738, which confirmed the model's predictive power.

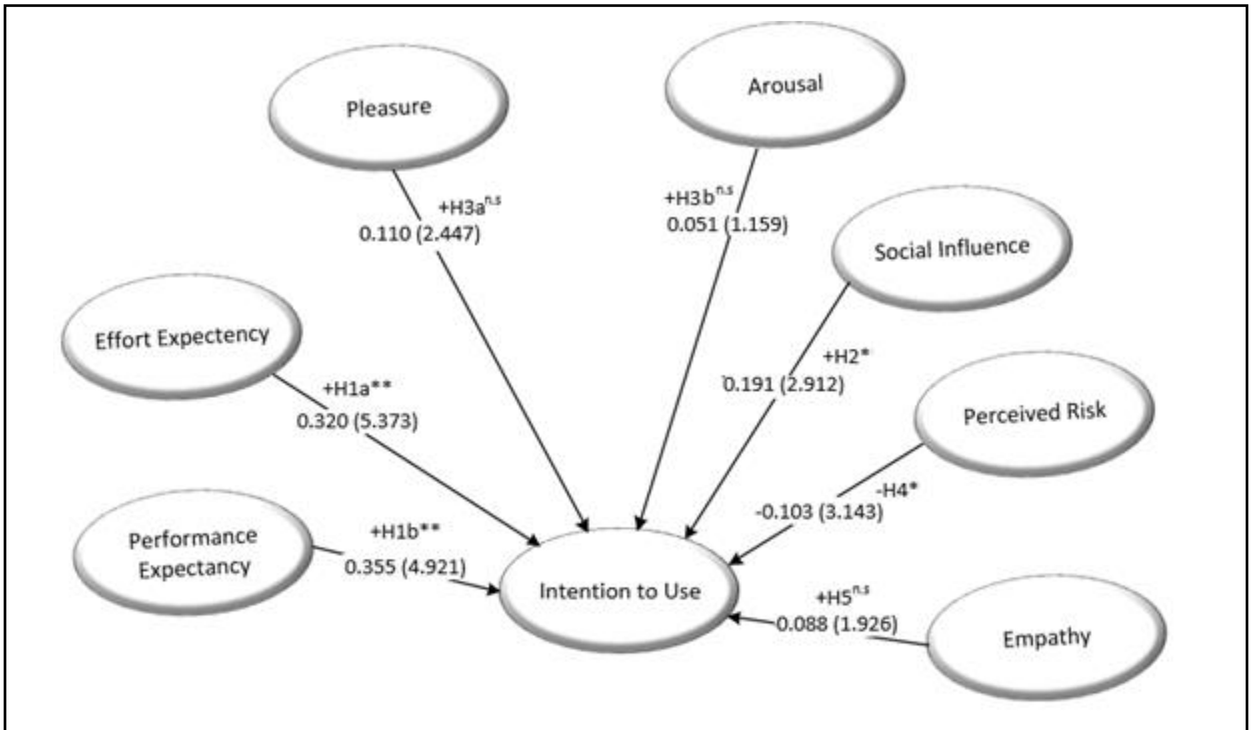
Finally, Stone-Geisser's Q^2 value is used to determine the predictive relevance of the structural model and it should be greater than 0 (Geisser, 1974; Stone, 1974). The Q^2 vale was 0.704, which confirmed the model's predictive relevance. The value of Q^2, R^2, t-value, path coefficient, and support of hypotheses are shown in Table 10.8, and the sign, magnitude, and significance of the path coefficients are shown in Figure 10.1.

Table 10.8 Path Coefficient of Robot Services Hypotheses

Variable	R^2	Q^2	Path Coefficient	t-value	Decision
Intention to use	0.738	0.704			
Arousal -> (+) Intention to use			0.051	1.159	Not supported
Effort Expectancy -> (+) Intention to use			0.320	5.373	Supported**
Empathy -> (+) Intention to use			-0.088	1.926	Not supported
Perceived Risk -> (+) Intention to use			-0.103	3.143	Supported*
Performance expectancy -> (+) Intention			0.355	4.921	Supported**
Pleasure -> (+) Intention to use			0.110	2.447	Not Supported
Social Influence -> (+) Intention to use			0.191	2.912	Supported*

*Significant at P**<0.001, P*<0.01.*

Figure 10.1 | Sign, Magnitude, and Significance of the Path Coefficients of Robot Surgeon Model



**p < 0.01, **p < 0.001; n.s. = not significant.*

10.3 Cyborg Service Model

10.3.1 Measurement Model Assessment

The results of the cyborg services measurement model confirmed the internal consistency reliability since the values of Cronbach's alpha and the composite reliability for all model constructs higher than 0.70. In addition, the standardized loading of the indicators was greater 0.70 and the t-values were greater than 1.96, to ensure the correct reliability indicator in the measurement model. Regarding convergent validity, all constructs of the cyborg services measurement model have AVE values greater than 0.50, which confirmed the convergent validity of the measurement model. Table 10.9 shows loading values, Cronbach's alpha, and Composite reliability values. For the discriminant validity evaluation, HTMT values were less than 0.90 for all constructs, and the square root of AVE value for each construct was higher than the correlation value with the other constructs (Table 10.10).

Table 10.9 Internal Consistency Reliability & Convergent Validity for Cyborg Services Measurement Model

Variable	Indicators	Loading	Cronbach's alpha	Composite reliability	AVE
Arousal	**CA1**	0.957	0.907	0.956	0.915
	CA2	0.956			
Effort Expectancy	**CEE1**	0.931	0.962	0.972	0.898
	CEE2	0.955			
	CEE3	0.951			
	CEE4	0.954			
Empathy	**CE1**	0.871	0.956	0.966	0.852
	CE2	0.897			
	CE3	0.947			
	CE4	0.958			
	CE5	0.939			
Intention to Use	**CIU1**	0.977	0.952	0.977	0.954
	CIU2	0.977			
Pleasure	**CP1**	0.952	0.883	0.945	0.895
	CP2	0.940			
Perceived Risk	**CPR1**	0.970	0.931	0.943	0.848
	CPR2	0.923			
	CPR3	0.867			
Performance Expectancy	**CPE1**	0.930	0.943	0.959	0.854
	CPE2	0.940			
	CPE3	0.938			
	CPE4	0.886			
Social Influence	**CSI1**	0.948	0.942	0.963	0.896
	CSI2	0.958			
	CSI3	0.935			

***CPE**: Cyborg Performance Expectancy, **CEE**: Cyborg Effort Expectancy**, CSI**: Cyborg Social Influence, **CPR**: Cyborg Perceived Risk, **CE**: Cyborg Empathy, **CA**: Cyborg Arousal, **CP**: Cyborg Pleasure, and **CIU**: Cyborg Intention to Use.*

Table 10.10 Discriminant validity of the Cyborg Services Measurement Model.

Variable	Arousal	Effort Expectancy	Empathy	Intention to use	Perceived Risk	Performance expectancy	Pleasure	Social Influence
Arousal	**0.957**	0.743	0.729	0.772	0.095	0.757	0.834	0.744
Effort	0.694	**0.948**	0.864	0.876	0.069	0.889	0.729	0.843
Empathy	0.679	0.829	**0.923**	0.735	0.201	0.797	0.678	0.817
Intention to use	0.717	0.840	0.702	**0.977**	0.059	0.849	0.721	0.819
Perceived Risk	0.106	0.087	0.197	0.074	**0.921**	0.151	0.100	0.165
Performance	0.703	0.852	0.761	0.810	0.163	**0.924**	0.686	0.880
Pleasure	0.748	0.675	0.626	0.663	0.101	0.632	**0.946**	0.691
Social Influence	0.688	0.803	0.776	0.776	0.189	0.831	0.633	**0.947**

Note: values on the main diagonal are the square roots of the AVEs, below the diagonal: correlations between the constructs, and above the diagonal: HTMT values.

10.3.2 Structural Model Assessment

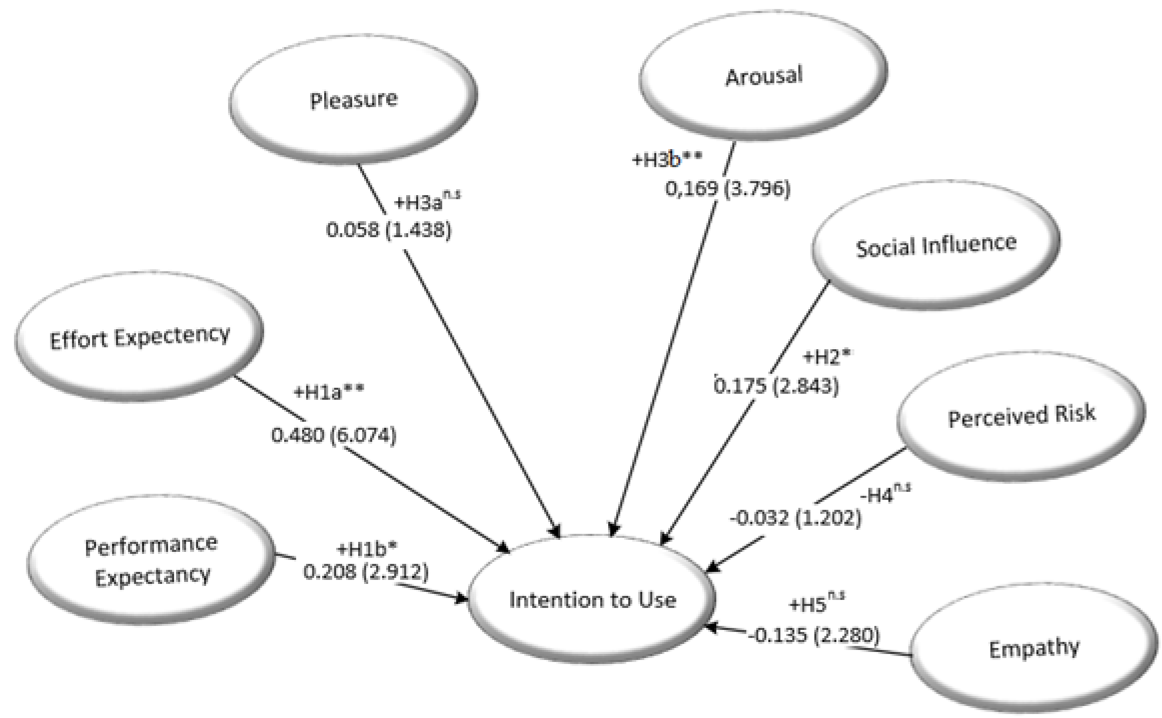
According to this research results for the cyborg services structural model, H1 (The influence of Effort Expectancy and Performance Expectancy), H2 (The influence of Social Influence), and H3b (The influence of Arousal) are supported. However, H3a (The influence of Pleasure), H4 (The influence of Empathy), and H5 (The influence of Perceived Risk) are rejected, since the path coefficient isn't significant ($0.01 < p$ and $t < 2.57$). Also, the R^2 value was 0.770, which confirmed the predictive power of the cyborg services model. Finally, Stone-Geisser's Q^2 value was 0.741, which confirmed the predictive relevance of the cyborg services model. The value of Q^2, R^2, p-value, t-value, path coefficient, and support of hypotheses are shown in Table 10.11, and the sign, magnitude, and significance of the path coefficients are shown in Figure 10.2.

Table 10.11 Path Coefficient of Cyborg Services Hypotheses

Variable	R^2	Q^2	Path Coefficient	t-value	Decision
Intention to use	0.770	0.741			
Arousal -> (+) Intention to use			0.169	3.796	Supported**
Effort Expectancy -> (+) Intention to use			0.480	6.074	Supported**
Empathy -> (+) Intention to use			-0.135	2.280	Not Supported
Perceived Risk -> (+) Intention to use			-0.032	1.202	Not Supported
Performance expectancy -> (+) Intention to			0.208	2.912	Supported*
Pleasure -> (+) Intention to use			0.058	1.438	Not Supported
Social Influence -> (+) Intention to use			0.175	2.843	Supported*

*Significant at P**<0.001, P*<0.01.*

Figure 10.2 | Sign, Magnitude, and Significance of the Path Coefficients of Cyborg Surgeon Model



**p < 0.01; *p < 0.001; n.s. = not significant*

10.4 Human Service Model

10.4.1 Measurement Model Assessment

Cronbach's alpha, composite reliability, standardized loading, and t-value had been used to evaluate the internal consistency reliability of the human services measurement model. All values were greater than the threshold values, which conformed the internal consistency of the measurement model. Moreover, AVE values were greater than 0.50, which confirmed the convergent validity of the measurement model. The AVE, Cronbach's alpha, composite reliability, and standardized loading values are shown in Table 10.12. On the other hand, the discriminant validity of the human services measurement model had been confirmed, since the values of HTMT were less than 0.90 for all constructs, and the square root of AVE value for each construct was higher than the correlation value with the other constructs. Table 10.13 shows the HTMT, square root of the AVE, and correlation values for all constructs.

Table10.12 Internal Consistency Reliability & Convergent Validity for Human Services Measurement Model

Variable	Indicators	Loading	Cronbach's alpha	Composite reliability	AVE
Arousal	**HA1**	0.944	0.892	0.949	0.903
	HA2	0.956			
Effort Expectancy	**HEE1**	0.959	0.972	0.979	0.921
	HEE2	0.964			
	HEE3	0.963			
	HEE4	0.954			
Empathy	**HE1**	0.898	0.957	0.967	0.855
	HE2	0.914			
	HE3	0.938			
	HE4	0.948			
	HE5	0.924			
Intention to Use	**HIU1**	0.975	0.948	0.975	0.951
	HIU2	0.975			
Pleasure	**HP1**	0.934	0.891	0.927	0.809
	HP2	0.911			
Perceived Risk	**HPR1**	0.943	0.912	0.938	0.791
	HPR2	0.934			
	HPR3	0.816			
Performance Expectancy	**HPE1**	0.904	0.826	0.92	0.851
	HPE2	0.919			
	HPE3	0.902			
	HPE4	0.828			
Social Influence	**HSI1**	0.965	0.958	0.973	0.922
	HSI2	0.963			
	HSI3	0.952			

***HPE**: Human Performance Expectancy, **HEE**: Human Effort Expectancy, **HSI**: Human Social Influence, **HPR**: Human Perceived Risk, **HE**: Human Empathy, **HA**: Human Arousal, **HP**: Human Pleasure, and **HIU**: Human Intention to Use*.

Table 10.13 Discriminant validity of the Human Services Measurement Model

Variable	Arousal	Effort Expectancy	Empathy	Intention to use	Perceived Risk	Performance expectancy	Pleasure	Social Influence
Arousal	**0.950**	0.505	0.603	0.544	0.364	0.634	0.749	0.531
Effort Expectancy	0.471	**0.960**	0.808	0.898	0.218	0.835	0.662	0.791
Empathy	0.556	0.780	**0.924**	0.756	0.37	0.807	0.753	0.795
Intention to use	0.503	0.863	0.721	**0.975**	0.217	0.817	0.652	0.792
Perceived Risk	0.319	0.220	0.351	0.226	**0.899**	0.303	0.352	0.331
Performance expectancy	0.568	0.804	0.763	0.775	0.277	**0.889**	0.737	0.833
Pleasure	0.645	0.596	0.674	0.580	0.314	0.646	**0.923**	0.665
Social Influence	0.490	0.763	0.762	0.755	0.326	0.784	0.596	**0.960**

Note: values on the main diagonal are the square roots of the AVEs, below the diagonal: correlations between the constructs, and above the diagonal: HTMT values.

10.4.2 Structural Model Assessment

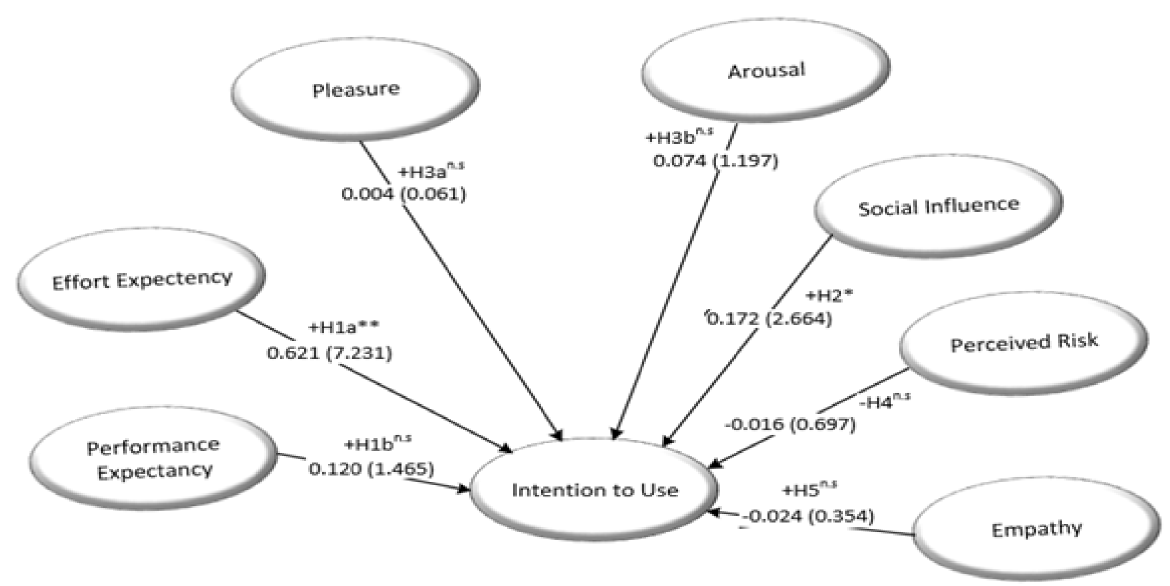
In addition to the path coefficient for exogenous variables, the human services structural model hypotheses had been tested by evaluating p-value and t-value among each exogenous variables and endogenous variable. According to that, H1a (The influence of Effort Expectancy) and H2 (Social Influence) are supported. However, H1b (The influence of Performance Expectancy), H3 (The influence of Arousal and Pleasure), H4 (The influence of Empathy), and H5 (The influence of Perceived Risk) were rejected, since the path coefficient was not significant (0.01 < p and t < 2.57). On the other hand, the model confirmed its predictive power and relevance, where R2 (0.777) and Q2 (0.738) values were greater than the threshold values. The structural model assessment of human services is shown in Table 10.14, and the sign, magnitude, and significance of the path coefficients are shown in Figure 10.3.

Table 10.14 Path Coefficient of Human Services Hypotheses

Variable	R^2	Q^2	Path Coefficient	t-value	Decision
Intention to use	0.777	0.738			
Arousal -> (+) Intention to use			0.074	1.197	Not supported
Effort Expectancy -> (+) Intention to			0.621	7.231	Supported**
Empathy -> (+) Intention to use			-0.024	0.354	Not Supported
Perceived Risk -> (+) Intention to use			-0.016	0.697	Not Supported
Performance expectancy -> (+)			0.120	1.465	Not Supported
Pleasure -> (+) Intention to use			0.004	0.061	Not Supported
Social Influence -> (+) Intention to use			0.172	2.664	Supported*

*Significant at P**<0.001, P**<0.01.*

Figure 10.3 | Sign, Magnitude, and Significance of the Path Coefficients of the Human Surgeon Model



**p < 0.01; **p < 0.001; n.s. = not significant*

10.5 Comparative Analysis

10.5.1 Measurement Invariance of Composite Models (MICOM) Analysis

This research followed the three-steps procedure to analyze the measurement invariance of composite models (MICOM). In the first step, this research confirmed the configural invariance between cyborg and robot models, cyborg and human models, and finally between robot and human models. Followed by the compositional invariance step, which has been confirmed as shown in Table 10.15 for cyborg and robot models, Table 10.16 for cyborg and human models, and in Table 10.17 for robot and human models. In most cases, the permutation p-values> 0.01 and the correlation between the composite scores between the groups is correct. Specifically, it is not met in the case of Performance Expectation for the comparison between robot vs. human, but since the correlations are very close to 1 this breach is not relevant since its value outside the confidence interval is due to small differences very close to 1. Since configural invariance (stage 1) and compositional invariance (stage 2) are met, we can say that there are no problems with measurement invariance. Then this research confirmed the partial measurement invariance by evaluating the third step (i.e. equality of composite means and variances) and as shown in Table 10.18, Table 10.19, and Table 10.20 for the abovementioned models.

Table 10.15 Cyborg-Robot Models Compositional Invariance Test

Variable	Original Correlation	5.0%	Permutation p-Values	Partial measurement invariance established
Arousal	1,000	1,000	0.672	Yes
Effort Expectancy	1,000	1,000	0.529	Yes
Empathy	1,000	1,000	0.441	Yes
Intention to use	1,000	1,000	0.123	Yes
Perceived Risk	0.959	0.219	0.623	Yes
Performance expectancy	1,000	1,000	0.462	Yes
Pleasure	1,000	0.999	0.370	Yes
Social Influence	1,000	1,000	0.187	Yes

Table 10.16 Cyborg-Human Models Compositional Invariance Test

Variable	Original Correlation	5.0%	Permutation p-Values	Partial measurement invariance established
Arousal	1,000	1,000	0.084	Yes
Effort Expectancy	1,000	1,000	0.968	Yes
Empathy	1,000	1,000	0.513	Yes
Intention to use	1,000	1,000	0.620	Yes
Perceived Risk	0.995	0.902	0.487	Yes
Performance expectancy	1,000	1,000	0.052	Yes
Pleasure	1,000	1,000	0.724	Yes
Social Influence	1,000	1,000	0.746	Yes

Table 10.17 Robot-Human Models Compositional Invariance Test

Variable	Original Correlation	5.0%	Permutation p-Values	Partial measurement invariance established
Arousal	1,000	1,000	0.031	Yes
Effort Expectancy	1,000	1,000	0.503	Yes
Empathy	1,000	1,000	0.438	Yes
Intention to use	1,000	1,000	0.240	Yes
Perceived Risk	0.971	-0.570	0.989	Yes
Performance expectancy	0.999	1,000	0.005	Yes
Pleasure	1,000	0.999	0.605	Yes
Social Influence	1,000	1,000	0.270	Yes

Table 10.18 Cyborg-Robot Models' Equality of Composite Means and Variances Test

Variable	Mean Difference	2.5% - 97.5%	Variance Difference	2.5% - 97.5%	Equal Mean/Variance	Measurement invariance
Arousal	0.289	-0.143 – 0.139	-0.141	-0.152 – 0.166	No/Yes	Partial
Effort Expectancy	0.541	-0.154 – 0.133	-0.090	-0.135 – 0.145	No/Yes	Partial
Empathy	0.633	-0.145 – 0.133	-0.124	-0.139 – 0.146	No/Yes	Partial
Intention to use	0.353	-0.154 – 0.144	-0.184	-0.133 – 0.138	No/No	Partial
Perceived Risk	-0.244	-0.137 – 0.153	-0.021	-0.145 – 0.155	No/Yes	Partial
Performance expectancy	0.292	-0.153 – 0.142	-0.211	-0.148 – 0.166	No/No	Partial
Pleasure	0.263	-0.141 – 0.132	-0.094	-0.154 – 0.160	No/Yes	Partial
Social Influence	0.333	-0.144 – 0.138	-0.154	-0.154 – 0.160	No/Yes	Partial

Table 10.19 Cyborg-Human Equality of Composite Means and Variances Test

Variable	Mean Difference	2.5% - 97.5%	Variance Difference	2.5% - 97.5%	Equal Mean/Variance	Measurement invariance
Arousal	-0.347	-0.139 – 0.137	0.142	-0.184 – 0.175	No/Yes	Partial
Effort Expectancy	-0.754	-0.128 – 0.145	0.326	-0.180 – 0.162	No/No	Partial
Empathy	-0.727	-0.130 – 0.140	0.282	-0.175 – 0.171	No/No	Partial
Intention to use	-0.646	-0.129 – 0.152	0.367	-0.181 – 0.167	No/No	Partial
Perceived Risk	-0.137	-0.136 – 0.149	-0.017	-0.150 – 0.155	No/Yes	Partial
Performance expectancy	-0.431	-0.133 – 0.143	0.266	-0.200 – 0.191	No/No	Partial
Pleasure	-0.486	-0.134 – 0.141	0.220	-0.173 – 0.177	No/No	Partial
Social Influence	-0.667	-0.134 – 0.152	0.124	-0.173 – 0.163	No/Yes	Partial

Table 10.20 Robot-Human Equality of Composite Means and Variances Test

Variable	Mean Difference	2.5% - 97.5%	Variance Difference	2.5% - 97.5%	Equal Mean/Variance	Measurement invariance
Arousal	-0.610	-0.157 – 0.140	0.283	-0.173 – 0.168	No/No	Partial
Effort Expectancy	-1.145	-0.137 – 0.156	0.416	-0.135 – 0.128	No/No	Partial
Empathy	-1.181	-0.141 – 0.139	0.406	-0.138 – 0.122	No/No	Partial
Intention to use	-0.917	-0.143 – 0.146	0.551	-0.152 – 0.152	No/No	Partial
Perceived Risk	0.252	-0.153 – 0.135	-0.137	-0.307 – 0.309	No/Yes	Partial
Performance expectancy	-0.684	-0.148 – 0.145	0.472	-0.181 – 0.163	No/No	Partial
Pleasure	-0.716	-0.146 – 0.147	0.315	-0.163 – 0.160	No/No	Partial
Social Influence	-0.913	-0.144 – 0.159	0.278	-0.153 – 0.156	No/No	Partial

10.5.2 Permutation Analysis

In this stage, this research used the permutation approach to compare among the proposed models. As shown in Table 10.21 for the comparative analysis between cyborg and robot models, there are no significant differences among the two models. Also, there are no significant differences between the cyborg and human service models regarding the relationship between independent variables and intention to use and as shown in Table 10.22. However, the robot and human service models have a significant difference, especially in the impact of effort expectancy (p-value <0.01) on the intention to use these services, as shown in Table 10.23.

Table 10.21 Permutation Test between Cyborg and Robot Models

Variable	Path Coefficients (Cyborg)	Path Coefficients (Robot)	Path Coefficients Difference	p-Values
Arousal	0.169	0.051	0.118	0.061
Effort Expectancy	0.480	0.320	0.160	0.097
Empathy	-0.135	-0.088	-0.048	0.526
Perceived Risk	-0.032	-0.103	0.071	0.112
Performance expectancy	0.208	0.355	-0.147	0.157
Pleasure	0.058	0.110	-0.052	0.379
Social Influence	0.175	0.191	-0.016	0.870

Table 10.22 Permutation Test between Cyborg and Human Models

Variable	Path Coefficients (Cyborg)	Path Coefficients (Human)	Path Coefficients Difference	p-Values
Arousal	0.169	0.074	0.095	0.245
Effort Expectancy	0.480	0.621	-0.140	0.250
Empathy	-0.135	-0.024	-0.111	0.251
Perceived Risk	-0.032	-0.016	-0.016	0.676
Performance expectancy	0.208	0.120	0.088	0.420
Pleasure	0.058	0.004	0.054	0.449
Social Influence	0.175	0.172	0.003	0.975

Table 10.23 Permutation Test between Robot and Human Models

Variable	Path Coefficients (Robot)	Path Coefficients (Human)	Path Coefficients Difference	p-Values
Arousal	0.051	0.074	-0.023	0.809
Effort Expectancy	0.320	0.621	-0.300	0.002
Empathy	-0.088	-0.024	-0.063	0.440
Perceived Risk	-0.103	-0.016	-0.087	0.070
Performance expectancy	0.355	0.120	0.235	0.012
Pleasure	0.110	0.004	0.106	0.160
Social Influence	0.191	0.172	0.019	0.837

PART IV: DISCUSSION AND CONCLUSION

Chapter 11: Conclusion, Implications, and Limitations

11.1 Conclusion and Implications

In spite that robotic technology predominantly exists in the market for different utilizations, it is also being developed for enhanced functions in areas such as healthcare services with the primary objective being able to utilize this technology to replicate a surgeon's tasks and perform independently without human intervention. In fact, different studies have investigated the acceptance of robots in terms of social interaction. However, the actual response of consumers towards service robots is still under investigation and little attention has been paid to this context (Stock & Merkle, 2018). Likewise, the acceptance of using cyborg technology, which is a result of combining the human biological body with insideables or/and wearables technologies, is still under investigation, and the acceptance of the services that could be offered by cyborg itself hasn't been investigated yet. In this context, nothing is known about the moral attitude of people toward the ratio between risk and benefits of using cyborg services and about their preferences, expectations, and needs (Schicktanz et al., 2015). On the other hand, it is clear that the robot and cyborg will evolve and alter the workforce and marketplace. What is unclear is the extent of this development and its impact, and how consumers will perceive them in service settings. Thus, the robot and cyborg service models have been developed to evaluate the patients' intention toward using them when compared mainly to human surgeons. The models have been built based on the technology acceptance models (e.g. UTAUT, TAM, and CAN models), in addition to integrating some of the other constructs that could be able to evaluate the proposed surgeon (i.e. robot and cyborg surgeons) and to be applied on the human surgeon choice criteria. In this way, the author of this research believes that the models will be able to assess the choice criteria among those surgeons.

This research performed ANOVA t-test in order to examine if there is a variance in the intention to use between the three models. The significant differences in the intention to use the proposed services have been confirmed. Moreover, the results showed that human surgeons are the preferred choice followed by cyborg and robot surgeons. These results were consistent with the results of the open questions, which have been used in the survey while collecting this research data. Also, the participants have been asked to justify their answers by mentioning the advantages and disadvantages of their first choice. Regarding the human surgeon choice, most of the participants' answers were related to the personal and professional traits of humans over the other choices. For instance, some of the participants believed that the accumulated experience of the human surgeons will make them better than proposed options in terms of skills and ability to act better in risky and unexpected situations during the surgery. Additionally, most of the participants believed that it will be easy for them to interact and communicate with the human surgeon. On the other side, participants mentioned a variety of drawbacks associated with the human surgeon, such as medical mistakes, surgeries time, availability, unexpected changes in the human mood, and aging. Most of the participants in this group chose the cyborg as a second option (i.e. 57%) and 23% chose robot as the third option, while the rest (20%) preferred human surgeons only. For the participants of the second group who considered cyborg surgeons as the preferred option, most of them mentioned the proposed ability of cyborg to avoid human mistakes as the main advantage of cyborg surgeons over human and robot surgeons. Likewise, they believed that enhanced human will be able to overcome human drawbacks, such as speed, memory, mood, aging, and physical capabilities. Some of the participants confirmed that cyborg surgeons will be their preferred choice because they expect these surgeons will be more accurate and efficient than human and robot surgeons. They believe the combination of technology and the human body will be a superior product. However, their concerns were related to the technological side of the cyborg. They considered the risk of unexpected failure in the technological parts of the cyborg could affect their safety. Also, some of them pointed to the high cost that could be associated with choosing this option. Meanwhile, the majority of this group considered human surgeons as their second preferred choice. Finally, the majority of participants who chose the robot surgeon over the other two options considered robot accuracy and mood stability as the main advantages of the machines over humans. However, the drawbacks of this option were about social interaction and technology failure risks. Most of the participants in the third group prioritized human surgeons as the second priority and the least priority were cyborgs. Another interesting result was related to the students of the medical sciences (6% of sample size) answers. As expected, 100% of those students preferred human surgeons as the first choice, but they considered cyborg as their second preferred choice. They believed that the proposed cyborg surgeons will have the ability to overcome human mistakes, will have better professional skills, and will improve surgeries duration. This part of society is important for such studies because they are representing the future human surgeons who will compete with cyborg and robot surgeons. Their thoughts about the need to improve human surgeon capabilities could give an impression of their willingness to accept to become a cyborg, the same as the majority of participants who gave cyborg the second priority behind the human surgeons. In general, these results showed that human services are still the preferred choice for the majority of Jordanian consumers, especially in healthcare services. Meanwhile, the impressions regarding cyborg services are promising, since the consumers believe that cyborgs will be able to solve the expected gap between human services and robot services in terms of healthcare mistakes, technological failures, speed, and interaction ability. In other words, the robot could be more accurate and faster than humans, but the potential risk of the robot's failure as a mechatronic device could affect negatively the consumers' intention to use it. In addition to robots' inability to interact with patients as much as human interaction ability. This could allow adopting the proposed cyborg services. At the same time, some of the participants raised a question about the chances of failures in the technological implants and the proposed impact of these failures on the service encounter. Nevertheless, both technologies are promising and consumers' acceptance of such technologies could be changed positively if the perceived benefits exceed risks (Pelegrín-Borondo et al., 2016; Satterfield et al., 2009).

Based on PLS-SEM results, the robot services model explained 73.8% of the variance in the intention to use robot healthcare services, 77.0% for the cyborg services model, and 77.7% for the human services model. This means, all the models of this research are highly predictive of the intention to use the related services. So far, the inclusion of emotional dimension, perceived risk, and empathy into this research model enhanced variance explained values (R^2) when compared, for instance to the values obtained by UTAUT (44%) and CAN (73.9%) models. These results confirmed the value of extending the factors that could determine the new technology acceptance by including the emotional dimensions of consumer behavior, consumer perceived risk, and empathy of robot, cyborg, and human.

The models assessed performance expectancy, effort expectancy, social influence, empathy, perceived risk, and emotions (Pleasure and arousal) variables. Four of the examined variables affected the intention to use robot service, except empathy and emotional dimensions. Hence, H1, H2, and H4 have been accepted, while H3 and H5 have been rejected. Also, four of the examined variables affected the intention to use cyborg services, except perceived risk, empathy, and pleasure. Therefore, H1, H2, and H3b have been accepted, but H3a, H4, and H5 have been rejected.

However, effort expectancy and social influence only affected the intention to use human services. So, H1a and H2 have been accepted, and the rest of the hypotheses have been rejected.

According to this research results, the effort expectancy showed the most significant impact on the intention to use robot and cyborg services, followed by the performance expectancy and in the positive direction (H1). Where both of them got the lowest p-value ($p<0.001$ for robot effort expectancy, robot performance expectancy, and cyborg effort expectancy, $p<0.01$ for cyborg performance expectancy). Meanwhile, effort expectancy has the highest t-value (Robot model= 5.373, Cyborg model = 6.074) and performance expectancy got a t-value of 4.921 for robot model and 2.912 for cyborg model, which represents the highest explanatory capacity for the robot services model. And for the cyborg services model, effort expectancy was in the first place and performance expectancy was in third place. This isn't surprising since many of the previous studies of robot technologies acceptance have agreed on the importance of these variables in stimulating the intention towards it (e.g. Alaiad & Zhou, 2013, 2014; Mucchiani et al., 2017; Stock & Merkle, 2017), and in cyborg acceptance studies too (e.g. Olarte-Pascual et al., 2015; Pelegrín-Borondo, Reinares-Lara, et al., 2017; Pelegrín-Borondo et al., 2016; Reinares-Lara et al., 2016). In addition to that, most of the differences in the importance of the two variables are related to the degree and the direction of their impact on the intention to use (Conti et al., 2017, 2015; Graaf et al., 2015; Park & Pobil, 2013). The importance of performance and effort expectancies could be justified because users could consider simplicity and performance efficiency as the most important factors that could stimulate their intention to use new technologies, especially during the early stages (Heerink et al., 2008a, 2009a, 2010a). Whilst, effort expectancy achieved the highest explained variance among the other variables for human services models (p-value <0.001, t-value=7.231), and the performance expectancy didn't show a significant impact on the intention to choose the human surgeon. The utilization of the said constructs in assessing choice criteria of human surgeons is new, which needs further investigation. Meanwhile, participants showed their attention to the simplicity of interacting with the human surgeon as the most important criterion. However, some of the previous studies pointed to the impact of surgeon performance history on the choice decision, especially when the patient is involved in the decision-making process. Contrariwise, those patients who aren't interested in being a part of the choice process may follow the recommendations from the referring physician and their relatives (Wilson et al., 2007). Generally, patients could interest in the interaction and communication with the physicians, not the surgeons.

According to that, the participants' responses to the effort and performance expectancies of the human surgeon could be a reflection of their perception of the proposed surgeons. In other words, the patients may not use the performance as a key criterion for choosing human services because they could believe in the fact that robots and cyborg surgeons will perform better. On the other side, patients may prefer to use human surgeons instead of robots because they could believe in the complexity of using and interacting with the robot surgeons. Finally, when compared to robot and cyborg service, further investigations on the impact of effort and performance expectancies on human services choice could be required.

The results showed that social influence (H2) has a positive significant impact on the intention to use robot, cyborg, and human services. It got a p-value of less than 0.01 for the three said models, a t-value equal to 2.912 for the robot model, 2.843 for the cyborg model, and 2.664 for the human services model. These results are in line with the previous studies about the robot's acceptance, where the direct interaction between humans and robots are involved (e.g. Conti et al., 2017; Heerink et al., 2009) and studies about being cyborg acceptance (e.g. Olarte-Pascual et al., 2015; Pelegrin-Borondo et al., 2017; Pelegrín-Borondo, Reinares-Lara, et al., 2017; Pelegrín-Borondo et al., 2016; Reinares-Lara et al., 2018, 2016; Zuniga et al., 2015) and for the human surgeon choice criteria studies, where the recommendations from family members, friends, and recommendations from the primary care physician have been considered as a major criterion while choosing the human surgeon (e.g. Ejaz et al., 2014; Yahanda et al., 2016). In general, individuals could change their feelings, thoughts, attitudes or behaviors when communicating with other individuals. Consequently, individuals could build their decisions based on other individuals' suggestions, especially when the service or product is relatively new and/or unknown (Talukder et al., 2019). Hence, the confirmed impact of social influence on the intention to use the proposed services can justify the importance of others' advice, especially for the proposed robot and cyborg services, which are still in the development stage.

The results didn't show a significant impact of pleasure and arousal emotions (H3) on the intention towards using the healthcare services that could be offered by the robots. Actually, pleasure is related to the direct interaction between humans and robots, which is expected to impact positively the patients' intention towards using the services. Also, adding human-like features into robots' designs such as face and voice features could stimulate the arousal emotions towards them (Chang, Wong, & Chu, 2018; Zhang et al., 2010, 2009). This could justify the results because the robot is still under development and it could be considered early to judge how the actual feature would look like and how such features will stimulate the arousal emotions, thereafter how the arousal will impact the consumers' intention to use those robots. Furthermore, the actual interaction between robots and humans could change the human perception of emotional pleasure. Meanwhile, it could be necessary to investigate the consumers' expectations of robot design in terms of appearance and communication abilities. Regarding the cyborg services model, the results confirmed the impact of arousal on the intention to use cyborg surgeons, but it didn't show a significant impact of pleasure emotions. Whereas, the explanatory capacity of arousal was in the second place and behind effort expectancy ($p<0.001$, $t=3.769$). In the services sector, consumers may require fulfilling their needs from two perspectives: performance and psychological perspectives. The psychological need is related to the consumer's emotions and its importance is dependent on the service nature. For instance, emotions could be considered a major criterion in hospitality services (Lu et al., 2019) and it could not impact surgeon choice (Yahanda et al., 2016). In the same context, pleasure is related to the hedonic motivation to adopt new technologies (Talukder et al., 2019). And since cyborg is a human with advanced capabilities, this could justify the results of cyborg and human services models, where the emotion construct didn't show a significant impact on the intention to choose human services.

The results also confirmed the negative impact of perceived risk (H4) on the intention to use robot services. The p-value was less than 0.01, and the t-value was 3.143, which makes its explanatory capacity in the third place and behind effort and performance expectancies impact. This is understood, since there is an implied uncertainty on the robots' appearance, consequent behavior, and its utility as a surgeon, which could justify the consumers' expectations on the risks that could be associated with human-robot interactions. Nevertheless, most of the previous researches in robot acceptance mentioned the importance of risk perception on new technology acceptance, but they didn't integrate it into their research models (e.g. Destephe et al., 2015; Matsui et al., 2018; Wirtz et al., 2018). Actually, patients could avoid the use of the services offered by robots if they believe there will be a risk associated with using those services (Blut et al., 2018), which make it one of the important factors that should be considered while studying the acceptance of robots, and as it has been confirmed by this research results. On the contrary, the perceived risk didn't show a significant impact on the intention to use cyborg and human services. In fact, few studies about insideables and wearables acceptance have integrated the perceived risk into their research models. For instance, Yang et al. (2016) studied the impact of perceived risk on the intention to use wearable technology and their research results confirmed its negative impact. Contrariwise, Murata, Arias-Oliva, and Pelegrín-Borondo (2019) didn't find a significant impact of the said construct on the acceptance to become a cyborg. In general, the inverse relation between expected benefits and risk could explain the results (Featherman, 2001; Gupta et al., 2015; Satterfield et al., 2009), because the cyborg is still a human with advanced capabilities that could be considered an opportunity to get better healthcare services, not a threat. In other words, patient perception of the cyborg benefits could reduce their perception of the associated risk while choosing cyborg surgeon (Gupta et al., 2015). Meanwhile, the human side of the proposed cyborg surgeon could reduce the perceived risk and uncertainty if the alternative is a technology (i.e. robots surgeon), which also could explain the results of the human services model.

Moreover, the result didn't show a significant impact of empathy (H5) on the intention to use for the whole research models. Actually, empathy is a skill that can be gained and developed and not a personal trait. However, in some service settings, it could be considered a significant driver of consumer purchase behavior, especially when direct interaction between employees and consumers is involved. Because the consumers in such settings expect the employee to understand their needs and to act accordingly (Malle & Pearce, 2001). Additionally, empathy has been integrated into the service quality model to investigate gaps between consumer expectations and perception of service quality (Purcarea et al., 2013). Likewise, as empathy has been considered a key component in the social interaction among humans, it has been applied to the social interaction between humans and robots too. This empathy can be transferred through facial expression during the interaction process (Riek & Robinson, 2008). The human perception of the robot's empathy could be influenced by the robot's behavior during the direct interaction between them (Gonsior et al., 2011). Furthermore, humans could not recognize the empathic behavior of the robots in the first use, rather they could concentrate on discovering the robot functionality (Carolis, Ferilli, & Palestra, 2017). In other words, the actual interaction between humans and robots could stimulate empathy perception toward robots and subsequently impact the human intention to use those robots (Kang, Kim, & Kwak, 2018). As well, in some service settings, professionalism could be considered the most important determinant of the choice criteria, such as in healthcare services, which could minimize the importance of empathy on the choice decision (Wu et al., 2015). Precisely, the impact of empathy could be significant while choosing primary care physicians and psychiatrists, not the surgeons (Dehning et al., 2014; Nadi et al., 2016), which also could justify the result for cyborg and human services models.

The results of the three models showed that the social influence and effort expectancy significantly affected the intention to use these surgical services, with a different intensity between the models for effort expectancy. The impact of social influence gives a general idea about the nature of the healthcare sector in Jordan, where a part of society gives more attention to the recommendation from others (e.g. family members and friends, users) while choosing their surgeons. And the effort expectancy impact contributes to patients' expectations of the simplicity, in terms of use and interaction with the proposed surgeons. On the other hand, the result of analyzing cyborg and human services models didn’t agree about the impact of perceived risk on the intention to use those services. On the contrary, the results of the robot services model confirmed the impact of perceived risk on the intention to use the robot surgeon. In this context, if the comparison is between cyborg and robot surgeons, this research results confirmed that a part of society is accepting those services with an advantage to the cyborg surgeon over the robot one. Therefore, maximizing the benefits of the cyborg services when compared to human services could make cyborgs the preferred choice for the consumers. These benefits could be in terms of speed, accuracy, and ability to interact with consumers. Regarding robots’ services, the main idea of using robots is to improve patient safety and to perform surgical care remotely, and to perform the entire surgery autonomously in the future. However, a part of society still believes in the risk that could be associated with using robot services. This risk could be a result of unexpected electro-mechanical faults, the potential of bleeding and infection probability during the surgeries, which may threaten the patient’s safety. This explained why the perceived risk showed a significant impact on the intention to use the proposed robot surgeon. Even though the choice of robot surgeon has been the least preferred option, it was accepted by a part of society. In order to improve the acceptance as per this research results, the perceived risk should be minimized by maximizing the benefits of using such technology (Gupta et al., 2015). Moreover, participants considered effort expectancy, performance expectancy, and social influence as the main choice criteria for robot services. Those benefits could be maximized by improving robot performance, simplifying its use, improving its interaction ability, and highlighting the said improvements to the consumers in a way that will be able to deliver the message to the consumers probably. Also, the results pointed to the importance of robot functionality over its social skills (i.e. empathy). This is understood because patients are interested in the ability of the robot surgeon to perform the surgery successfully and safely. Ultimately, the acceptance of the proposed robot technology and cyborg technology by a part of the society could give an idea about the expected struggle in the future among developing robots and enhancing human capabilities. Even though some of the researchers supporting the idea of directing effort and resources to develop the implants technology to enhance humans, instead of consuming time and energy to develop robots that could go beyond human abilities and intelligence. The fears of human extinction because of robots reinforce their belief about the ability of human enhancements to face those fears (Fox, 2018).

Partial Least Squares Multi-Group Analysis has been applied to measure whether there are differences in the way variables affect the intention to use the proposed services. The first multi-group analysis has been applied between cyborg and robot models using the permutation approach (Henseler et al., 2016). The results confirmed that the models' variables are affecting the intention to use cyborg and robot services in the same way. This is could be justified, since the result of both models confirmed a similarity in the impact of most of the variables on the intention to use those services, except for perceived risk and emotional dimensions. Where perceived risk has a significant impact on the intention to use robot services, not cyborg services. In addition to that, the perceived risk impact on robot services was small when compared to effort expectancy and performance expectancy, and the difference in the standardized loadings between the two models was low (0.071 points). Nevertheless, further investigations are required regarding the perceived risk impact, because some of the previous studies agreed on its impact on the behavioral intention, such as for being cyborg acceptance for Pelegrin-Borondo et al. (2017). Whereas, in their study about social robot acceptance, Blut et al. (2018) confirmed the impact of perceived risk through its impact on the trust dimension, which could require future studies to investigate the impact of trust dimension on the relation between perceived risk and intention to use robot and cyborg services. This could be applied to human services too since the perceived risk didn’t show a significant impact on intention to use, and no significant differences were found for perceived risk impact on intention to use human vs cyborg services, and human vs robot services. On the other side, arousal showed a significant impact on cyborg services only, and the differences between cyborg vs robot, and cyborg vs human services were low and not significant. Regarding pleasure, it didn’t show a significant impact on the three services and the differences between the models were low. Also, the multi-group analysis didn’t show significant differences among cyborg and human services models regarding the relationship between independent variables and intention to use. Where the impact of effort expectancy and social influence on both models was almost the same, so no significant differences have been confirmed. Despite that the performance expectancy showed only a significant impact on robot and cyborg services, the multi-group analysis didn't confirm a significant difference in its impact on intention to use among cyborg and human services, and intention to use among cyborg and robot services. The differences were low in order to be considered significant. However, the differences between robot and human service models existed in the relation between effort expectancy and intention to use only. Regarding the effort expectancy, its impact was higher for human services (β=0.621) than for robot services. This result could justify participants' belief about the simplicity of interacting and communicating with human surgeons over robot surgeons while answering the open-ended questions. These results may not weaken the impact of effort expectancy on the robot acceptance, rather they indicate its importance in stimulating or inhibiting the acceptance process. More specifically, the failure of effort expectancy perception by consumers could impact negatively their intention toward using robot services, and they may prefer the human ones instead (Guo et al., 2012; Lai, 2014; Lee & Rho, 2013; Sun et al., 2013). On the other hand, this could require robot technology developers to draw more attention to the interaction ability of robots, especially for autonomous applications, where the robot is expected to perform the tasks independently without human intervention. Despite that, the performance expectancy impact was confirmed for robot services (β=0.355) and wasn't confirmed for human services, the differences between the two models were low to be considered significant. This is understood because consumers' expectations toward robot's performance could be affected by their perceptions of other factors, such as perceived risks, which is highlighting the importance of the relationship between expected benefits and potential risk (Featherman, 2001; Gupta et al., 2015; Satterfield et al., 2009). Nevertheless, the expectations of hiring new technologies are related to enhancing job or task outcomes when compared to the traditional ways, where the human is the dominant one. Accordingly, different studies in the literature have confirmed the importance of performance expectancy in stimulating new technology acceptance when compared to human performance, especially in the long run (Heerink et al., 2008a, 2009a, 2010a), such as in robot technology acceptance (Alaiad & Zhou, 2013, 2014; Conti et al., 2017, 2015; Graaf et al., 2015; Mucchiani et al., 2017; Park & Pobil, 2013; Stock & Merkle, 2017).

According to that, further investigations are required, especially when the interaction between consumers and proposed surgeons will be taken place.

This research opens a new line of researches related to the acceptance of cyborg technology as an entity and robot as an autonomous device that could be used in critical service settings (i.e. medical surgeries). With regards to cyborg technology, few studies have been conducted to investigate cyborg acceptance, which helped the companies in promoting their related products (i.e. wearables and implants), and to understand the factors stimulating the acceptance of those products. At the same time, the acceptance of the proposed cyborg services will help the service providers to know the factors that can lead to the acceptance of hiring cyborg in a specific service setting. According to that, the developers and manufacturers of cyborg products can build their design based on consumers' expectations of these enhancements and match their needs. For instance, the result of cyborg services confirmed the impact of effort expectancy, performance expectancy, social influence, and arousal on the acceptance of the proposed cyborg services. Spreading awareness about the simplicity in dealing and interacting with cyborgs and the superiority of their performance will be required to convince the society about accepting the cyborg services. In addition to that, the idea of the possibility of being served by an enhanced human could make consumers excited to try it. This consequently requires reinforcing those emotions by promoting cyborg superior abilities. The same should be done with robot services too with considering the impact of risk perception. A practical solution to minimize expected risk could enhance people's perception toward such robots, which needs further investigation and development in the robot's design. In addition to creating marketing campaigns about the benefits of using the proposed services, which may help to instill more confidence in this technology, thereby consumers' risk perception could be minimized.

11.2 Limitations

One of the research limitations is related to investigate the ethical impact while studying the acceptance of such technologies. The robot and cyborg surgeons are representing an advanced technology that may have the ability to imitate and/or exceed human abilities. If these futuristic surgeons become a reality, they will compete with human surgeons and could eventually replace them. Thereby, increasing the professional and social gap between humans from one side, robots and enhanced humans on the other side. Another ethical concern is, if these advanced surgeons are available for high-income consumers, it could create a new social class that can buy the proposed superior services. This could consequently increase the equity gap too. Furthermore, the study has been conducted in a single country. The differences in culture could affect consumers' intentions toward those technologies. According to that, this research should be extended to different countries for evaluating the impact of cultural differences on the intention to use the proposed services. In addition, consumers' knowledge about cyborg technology and robot applications is limited. Therefore, this research results represented a general belief of the consumers about advanced technologies. Even though the proposed services are still under the development stage, enhancing respondents' awareness about these technologies could affect their perception toward the proposed services. Consequently, future research could investigate whether providing participants more information about those technologies before the data collection process - through, for instance, video demonstrations and prototypes – can impact their perception towards these services and their intention to adopt them. In the same context, this research proposed a specific use of cyborg and robot technologies. The result could vary if the proposed use conducted in different service settings. Therefore, future research could apply this research model to different service settings. On the other hand, further integration of service quality dimensions could be required in future research, since the service itself can control the intention of the consumers toward using it. Also, the humans' expectations toward the quality of these services could impact their attitude, intention, and use behavior (Cronin et al., 2000; Rahman, Mannan, Hossain, & Zaman, 2018; Song, 2017).

PART V: REFERENCES AND ANNEXES

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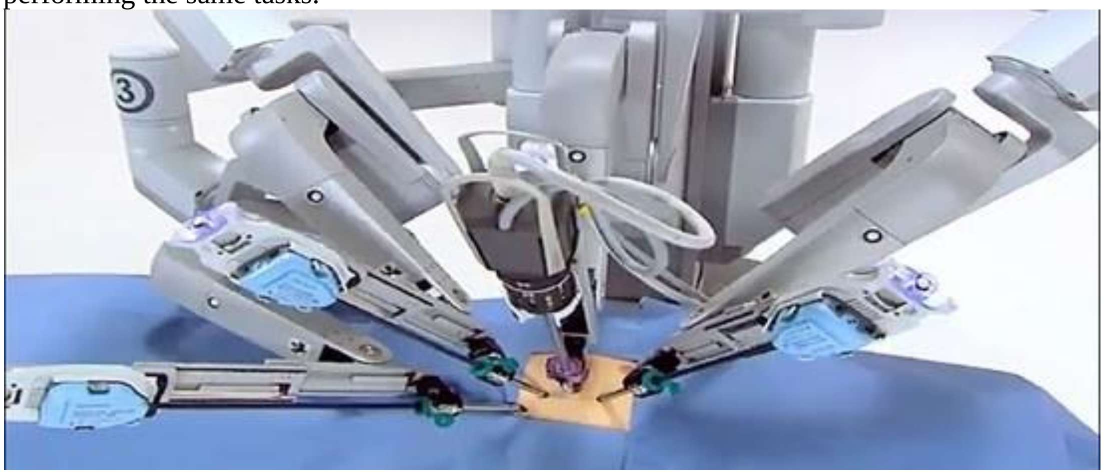
Annexes

Survey

* Required

A cyborg is a human with technological devices implanted in their body to improve their capacities over their innate ones (for example, improved memory, speed of calculation, or physical abilities). A robot is a programmable machine capable of performing certain operations autonomously and replacing humans in some tasks. What do you think about a surgery being undertaken by a human, a cyborg, or a robot? We are conducting a study about the choice between a human doctor, a cyborg doctor, and a robot for medical services. For instance, think about a surgery to correct a deficiency in one of your eyes.

According to recent news published in Newsweek magazine, the Smart Tissue Autonomous Robot (STAR), a robot to do surgery, has been proved as a more precise than expert human surgeons performing the same tasks.



There are no right or wrong answers. Your opinion is very important and will be treated anonymously for a university study. We do appreciate your collaboration. Thank you for participating (the survey will take about 10 minutes to be completed). (next page)

Section 1: Robot Services - Part 1

1.1 Consider that a Robot doctor could to do a surgery to correct a deficiency in one of your eyes. Indicate the extent to which you agree or disagree with the following statements on a scale of 0 (strongly disagree) to 10 (strongly agree), 5 being neither agree nor disagree:

1. 1.1.1 I will try to use services offered by a Robot Doctor for a surgery to correct a deficiency in my eye. *

   Mark only one oval.

0	1	2	3	4	5	6	7	8	9	10
⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭

2. 1.1.2 I predict that I will use services offered by a Robot Doctor for a surgery to correct a deficiency in my eye. *

Mark only one oval.

0	1	2	3	4	5	6	7	8	9	10
⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭

3. 1.1.3 For a surgery to correct a deficiency in my eye, learning to relate with a Robot Doctor will be easy for

me *

Mark only one oval.

0	1	2	3	4	5	6	7	8	9	10
⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭

4. 1.1.4 My interaction with a Robot Doctor will be clear and understandable. *

Mark only one oval.

0	1	2	3	4	5	6	7	8	9	10
⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭

5. 1.1.5 For me, interacting with a Robot Doctor will be easy. *

Mark only one oval.

0	1	2	3	4	5	6	7	8	9	10
⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭

6. 1.1.6 It will be easy for me to be good at interacting with a Robot Doctor. *

Mark only one oval.

0	1	2	3	4	5	6	7	8	9	10

7. 1.1.7 For a surgery to correct a deficiency in my eye, I will find the services offered by a Robot Doctor useful. *

Mark only one oval.

0	1	2	3	4	5	6	7	8	9	10

8. 1.1.8 The medical services offered by Robot Doctor will increase my chances of achieving things that are important to me. *

Mark only one oval.

0	1	2	3	4	5	6	7	8	9	10

9. 1.1.9 Using medical services offered by Robot Doctor will help me to accomplish things more quickly. *

Mark only one oval.

0	1	2	3	4	5	6	7	8	9	10

10. 1.1.10 The use of medical services offered by a Robot Doctor will let me use my resources more efficiently (time, money, etc.). *

Mark only one oval.

0	1	2	3	4	5	6	7	8	9	10

11. 1.1.11 For a surgery to correct a deficiency in my eye, people who influence my behavior think that I should use medical services offered by a Robot Doctor. *

Mark only one oval.

0	1	2	3	4	5	6	7	8	9	10

12. 1.1.12 People who are important to me think that I should use medical services offered by a Robot Doctor.
*

Mark only one oval.

0	1	2	3	4	5	6	7	8	9	10

13. 1.1.13 People whose opinions that I value, prefer that I should use medical services offered by Robot
Doctor. *

Mark only one oval.

0	1	2	3	4	5	6	7	8	9	10

14. 1.1.14 For a surgery to correct a deficiency in my eye, the services offered by Robot Doctor are risky. *

Mark only one oval.

0	1	2	3	4	5	6	7	8	9	10

15. 1.1.15 There is too much uncertainty associated with the services offered by a Robot Doctor. *

Mark only one oval.

0	1	2	3	4	5	6	7	8	9	10
⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭

16. 1.1.16 Compared with other methods of medical services, the service offered by Robot Doctor is riskier. *

Mark only one oval.

0	1	2	3	4	5	6	7	8	9	10
⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭

17. 1.1.17 For a surgery to correct a deficiency in my eye, a Robot Doctor will have a high level of empathy with respect to my needs as a client. *

Mark only one oval.

0	1	2	3	4	5	6	7	8	9	10
⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭

18. 1.1.18 A Robot Doctor will have no difficulty in determining my needs. *

Mark only one oval.

0	1	2	3	4	5	6	7	8	9	10
⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭

19. 1.1.19 A Robot Doctor will try to determine my needs by adopting my perspective. *

Mark only one oval.

0	1	2	3	4	5	6	7	8	9	10
⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭

20. 1.1.20 A Robot Doctor will find it easy to adopt my perspective as a client. *

Mark only one oval.

0	1	2	3	4	5	6	7	8	9	10
◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯

21. 1.1.21 A Robot Doctor will adapt its interactions to my needs in different situations. *

Mark only one oval.

0	1	2	3	4	5	6	7	8	9	10
◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯

Section 1: Robot Services - Part 2

1.2 On a scale of 0 to 10, indicate the extent to which the following descriptions reflect your feeling about using Robot Services. For example, in the first item, 0 would mean you Feel Unhappy with Robot services, and 10 would mean you feel Happy: When I think of the service being provided by a Robot, I feel:

22. 1.2.1 *

Mark only one oval.

	0	1	2	3	4	5	6	7	8	9	10	
Unhappy	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	Happy

23. 1.2.2 *

Mark only one oval.

	0	1	2	3	4	5	6	7	8	9	10	
Annoyed	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	Pleased

24. 1.2.3 *

Mark only one oval.

	0	1	2	3	4	5	6	7	8	9	10	
Relaxed												Stimulated

25. 1.2.4 *

Mark only one oval.

	0	1	2	3	4	5	6	7	8	9	10	
Calm												Excited

Section 2: Cyborg Services - Part 1

A cyborg is a human with technological devices implanted in their body to improve their capacities over their innate ones (for example, improved memory, speed of calculation, or physical abilities).

6.4 Consider that a Cyborg doctor could to do a surgery to correct a deficiency in one of your eyes. Indicate the extent to which you agree or disagree with the following statements on a scale of 0 (strongly disagree) to 10 (strongly agree), 5 being neither agree nor disagree:

1. 2.1.1 I will try to use services offered by a Cyborg Doctor for a surgery to correct a deficiency in my eye. *

Mark only one oval.

0	1	2	3	4	5	6	7	8	9	10

2. 2.1.2 I predict that I will use services offered by a Cyborg Doctor for a surgery to correct a deficiency in my eye. *

Mark only one oval.

0	1	2	3	4	5	6	7	8	9	10

3. 2.1.3 For a surgery to correct a deficiency in my eye, learning to relate with a Cyborg Doctor will be easy for

me *

Mark only one oval.

0	1	2	3	4	5	6	7	8	9	10
⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭

4. 2.1.4 My interaction with a Cyborg Doctor will be clear and understandable. *

Mark only one oval.

0	1	2	3	4	5	6	7	8	9	10
⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭

5. 2.1.5 For me, interacting with a Cyborg Doctor will be easy. *

Mark only one oval.

0	1	2	3	4	5	6	7	8	9	10
⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭

6. 2.1.6 It will be easy for me to be good at interacting with a Cyborg Doctor. *

Mark only one oval.

0	1	2	3	4	5	6	7	8	9	10
⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭

7. 2.1.7 For a surgery to correct a deficiency in my eye, I will find the services offered by a Cyborg Doctor useful. *

Mark only one oval.

0	1	2	3	4	5	6	7	8	9	10
⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭

8. 2.1.8 The medical services offered by Cyborg Doctor will increase my chances of achieving things that are important to me. *

Mark only one oval.

0	1	2	3	4	5	6	7	8	9	10
⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭

9. 2.1.9 Using medical services offered by Cyborg Doctor will help me to accomplish things more quickly. *

Mark only one oval.

0	1	2	3	4	5	6	7	8	9	10
⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭

10. 2.1.10 The use of medical services offered by a Cyborg Doctor will let me use my resources more efficiently (time, money, etc.). *

Mark only one oval.

0	1	2	3	4	5	6	7	8	9	10
⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭

11. 2.1.11 For a surgery to correct a deficiency in my eye, people who influence my behavior think that I should use medical services offered by a Cyborg Doctor. *

Mark only one oval.

0	1	2	3	4	5	6	7	8	9	10
⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭

12. 2.1.12 People who are important to me think that I should use medical services offered by a Cyborg Doctor.

*

Mark only one oval.

0	1	2	3	4	5	6	7	8	9	10
⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭

13. 2.1.13 People whose opinions that I value, prefer that I should use medical services offered by Cyborg
Doctor. *

Mark only one oval.

0	1	2	3	4	5	6	7	8	9	10
⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭

14. 2.1.14 For a surgery to correct a deficiency in my eye, the services offered by Cyborg Doctor are risky. *

Mark only one oval.

0	1	2	3	4	5	6	7	8	9	10
⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭

15. 2.1.15 There is too much uncertainty associated with the services offered by a Cyborg Doctor. *

Mark only one oval.

0	1	2	3	4	5	6	7	8	9	10
⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭

16. 2.1.16 Compared with other methods of medical services, the service offered by Cyborg Doctor is riskier. *

Mark only one oval.

0	1	2	3	4	5	6	7	8	9	10
⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭

17. 2.1.17 For a surgery to correct a deficiency in my eye, a Cyborg Doctor will have a high level of empathy with respect to my needs as a client. *

Mark only one oval.

0	1	2	3	4	5	6	7	8	9	10
⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭

18. 2.1.18 A Cyborg Doctor will have no difficulty in determining my needs. *

Mark only one oval.

0	1	2	3	4	5	6	7	8	9	10
⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭

19. 2.1.19 A Cyborg Doctor will try to determine my needs by adopting my perspective. *

Mark only one oval.

0	1	2	3	4	5	6	7	8	9	10
⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭

20. 2.1.20 A Cyborg Doctor will find it easy to adopt my perspective as a client. *

Mark only one oval.

0	1	2	3	4	5	6	7	8	9	10
⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭

21. 2.1.21 A Cyborg Doctor will adapt its interactions to my needs in different situations. *

Mark only one oval.

0	1	2	3	4	5	6	7	8	9	10
⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭

Section 2: Cyborg Services - Part 2

2.2 On a scale of 0 to 10, indicate the extent to which the following descriptions reflect your feeling about using Cyborg Services. For example, in the first item, 0 would mean you Feel Unhappy with Cyborg services, and 10 would mean you feel Happy: When I think of the service being provided by a Cyborg, I feel:

1. 2.2.1 *

Mark only one oval.

	0	1	2	3	4	5	6	7	8	9	10	
Unhappy	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	Happy

2. 2.2.2 *

Mark only one oval.

	0	1	2	3	4	5	6	7	8	9	10	
Annoyed	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	Pleased

3. 2.2.3 *

Mark only one oval.

	0	1	2	3	4	5	6	7	8	9	10	
Relaxed	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	Stimulated

4. 2.2.4 *

Mark only one oval.

	0	1	2	3	4	5	6	7	8	9	10	
Calm	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	Excited

Section 3: Human Services - Part 1

3.1 Consider that a Human doctor could to do a surgery to correct a deficiency in one of your eyes. Indicate the extent to which you agree or disagree with the following statements on a scale of 0 (strongly disagree) to 10 (strongly agree), 5 being neither agree nor disagree:

1. 3.1.1 I will try to use services offered by a Human Doctor for a surgery to correct a deficiency in my eye. *

Mark only one oval.

0	1	2	3	4	5	6	7	8	9	10
◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯

2. 3.1.2 I predict that I will use services offered by a Human Doctor for a surgery to correct a deficiency in my eye. *

Mark only one oval.

0	1	2	3	4	5	6	7	8	9	10
◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯

3. 3.1.3 For a surgery to correct a deficiency in my eye, learning to relate with a Human Doctor will be easy for

me *

Mark only one oval.

0	1	2	3	4	5	6	7	8	9	10
◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯

4. 3.1.4 My interaction with a Human Doctor will be clear and understandable. *

Mark only one oval.

0	1	2	3	4	5	6	7	8	9	10
⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭

5. 3.1.5 For me, interacting with a Human Doctor will be easy. *

Mark only one oval.

0	1	2	3	4	5	6	7	8	9	10
⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭

6. 3.1.6 It will be easy for me to be good at interacting with a Human Doctor. *

Mark only one oval.

0	1	2	3	4	5	6	7	8	9	10
⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭

7. 3.1.7 For a surgery to correct a deficiency in my eye, I will find the services offered by a Human Doctor useful. *

Mark only one oval.

0	1	2	3	4	5	6	7	8	9	10
⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭

8. 3.1.8 The medical services offered by Human Doctor will increase my chances of achieving things that are important to me. *

Mark only one oval.

0	1	2	3	4	5	6	7	8	9	10
⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭

9. 3.1.9 Using medical services offered by Human Doctor will help me to accomplish things more quickly. *

Mark only one oval.

0	1	2	3	4	5	6	7	8	9	10

10. 3.1.10 The use of medical services offered by a Human Doctor will let me use my resources more efficiently (time, money, etc.). *

Mark only one oval.

0	1	2	3	4	5	6	7	8	9	10

11. 3.1.11 For a surgery to correct a deficiency in my eye, people who influence my behavior think that I should use medical services offered by a Human Doctor. *

Mark only one oval.

0	1	2	3	4	5	6	7	8	9	10

12. 3.1.12 People who are important to me think that I should use medical services offered by a Human Doctor.
*

Mark only one oval.

0	1	2	3	4	5	6	7	8	9	10

13. 3.1.13 People whose opinions that I value, prefer that I should use medical services offered by Human
Doctor. *

Mark only one oval.

0	1	2	3	4	5	6	7	8	9	10
⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭

14. 3.1.14 For a surgery to correct a deficiency in my eye, the services offered by Human Doctor are risky. *

Mark only one oval.

0	1	2	3	4	5	6	7	8	9	10
⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭

15. 3.1.15 There is too much uncertainty associated with the services offered by a Human Doctor. *

Mark only one oval.

0	1	2	3	4	5	6	7	8	9	10
⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭

16. 3.1.16 Compared with other methods of medical services, the service offered by Human Doctor is riskier. *

Mark only one oval.

0	1	2	3	4	5	6	7	8	9	10
⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭

17. 3.1.17 For a surgery to correct a deficiency in my eye, a Human Doctor will have a high level of empathy with respect to my needs as a client. *

Mark only one oval.

0	1	2	3	4	5	6	7	8	9	10
⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭

18. 3.1.18 A Human Doctor will have no difficulty in determining my needs. *

Mark only one oval.

0	1	2	3	4	5	6	7	8	9	10
◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯

19. 3.1.19 A Human Doctor will try to determine my needs by adopting my perspective. *

Mark only one oval.

0	1	2	3	4	5	6	7	8	9	10
◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯

20. 3.1.20 A Human Doctor will find it easy to adopt my perspective as a client. *

Mark only one oval.

0	1	2	3	4	5	6	7	8	9	10
◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯

21. 3.1.21 A Human Doctor will adapt its interactions to my needs in different situations. *

Mark only one oval.

0	1	2	3	4	5	6	7	8	9	10
◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯

Section 1: Human Services - Part 2

3.2 On a scale of 0 to 10, indicate the extent to which the following descriptions reflect your feeling about using Human Services. For example, in the first item, 0 would mean you Feel Unhappy with Human services, and 10 would mean you feel Happy: When I think of the service being provided by a Human, I feel:

1. 3.2.1 *

Mark only one oval.

	0	1	2	3	4	5	6	7	8	9	10	
Unhappy												Happy

2. 3.2.2 *

Mark only one oval.

	0	1	2	3	4	5	6	7	8	9	10	
Annoyed												Pleased

3. 3.2.3 *

Mark only one oval.

	0	1	2	3	4	5	6	7	8	9	10	
Relaxed												Stimulated

4. 3.2.4 *

Mark only one oval.

	0	1	2	3	4	5	6	7	8	9	10	
Calm												Excited

General Question

1. Who would you prefer to carry out surgery to correct a deficiency in one of your eyes? *

Mark only one oval.

- A Human doctor
- A Cyborg doctor
- A Robot doctor

2. Based on your choice in the previous question, a)What are the advantages you find in your preferred option? *

b) What are the drawbacks you find in your preferred option? *

3. Who would you prefer as your second option to carry out surgery to correct a deficiency in one of your eyes? *

Mark only one oval.

- A Human
- doctor A
- Cyborg

doctor

A Robot doctor

Finally, we would appreciate it if you could provide some personal information to assist our statistical analysis. Please be assured that all data will be treated anonymously and confidentially.

1) Sex *

Mark only one oval.

- MAle
- Female

2) Age *

____

3) What is your study level? *

Mark only one oval.

- Associate degree.
- Bachelor
- Master
- PhD

4) What is your field of study? *

____

5) Where are you from (Country)? *

6) What is the name of your University (Institution)? *

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