UNIVERSIDADE CATÓLICA PORTUGUESA

Artificial Intelligence Acceptance: Morphological elements of the acceptance of Artificial Intelligence

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Resumo

A Inteligência Artificial tem-se desenvolvido muito rapidamente ao longo dos últimos anos, há medida que os algoritmos de *machine learning* vão evoluindo e ficando mais complexos, os robôs ficam cada vez mais autónomos, levando a um desenvolvimento mais rápido e à aparição de mais *chatbots* no suporte a variados serviços e assistentes pessoais como a Cortana e a Siri.

Esta rápida evolução permite que as empresas que adotam estas tecnologias possam vir a ganhar uma vantagem competitiva. No entanto, para que estas tecnologias se traduzam numa melhoria da *performance* das empresas, é de elevada importância que a Inteligência Artificial seja aceite e incentivada pelos colaboradores das empresas em questão.

Neste sentido, estudámos as teorias de aceitação da tecnologia existentes, adaptando o *UTAUT* para chegar a um novo modelo que permite compreender a aceitação de Inteligência Artificial. O instrumento de recolha de dados utilizado foi um questionário *online* que foi respondido por 321 pessoas com uma média de idades de aproximadamente 29 anos, sendo que cerca de 50% da amostra corresponde a pessoas com idades compreendidas entre os 22 e os 35 anos.

Os resultados obtidos foram bastante positivos, mostrando que a maioria das pessoas parece estar recetiva a esta tecnologia e achar que se trata de uma ferramenta útil.

Palavras-chave: Inteligência Artificial, teorias de aceitação da tecnologia

Abstract

Artificial Intelligence is experiencing a fast progress in the last years, as machine learning algorithms evolve into more complex algorithms, robots gain autonomy, leading to a faster development of chatbots in the support to several services and personal assistants, such as Cortana and Siri.

This rapid evolution allows companies to obtain competitive advantages by adopting this type of technologies. However, in order for these technologies to improve the companies' performance, employers, managers and employees have to accept Artificial Intelligence and foster the usage of these programs.

In this sense, we studied the existent technology acceptance theories, adapting the UTAUT to develop a model to study the acceptance of Artificial Intelligence. The instrument for collecting data used was an online questionnaire, that was answered by 321 people with an average of ages of approximately 29 years and 50% of the sample had ages between 22 and 35 years.

The results were very positive, showing that the generality of people seemed to be receptive to this technology, while thinking it can be an useful tool.

Keywords: Artificial Intelligence, technology acceptance theories

Content

List of Abbreviations

AI: Artificial Intelligence

AIC: Akaike Information Criterion

AIML: Artificial Intelligence Mark-up Language

ALICE: Artificial Linguistic Internet Computer Entity

CAPS: Cognitive-affective processing system

CAUs: cognitive-affective units

CMC: Computer-mediated communication

DS: Design Science

DTPB: Decomposed Theory of Planned Behaviour

EE: Effort expectancy

FC: Facilitating conditions

G: Gender

H: Habit

HM: Hedonic motivation

IDT: Innovation Diffusion Theory

IG: Imitation game

IoT: Internet of Things

MM: Motivational Model

PC: Personal Computers

PE: Performance expectancy

PEOU: Perceived ease of use

PU: Perceives usefulness

PV: Price value

R^2: Squared error

SCT: Social Cognitive Theory

SI: Social influence

TAM: Technology Acceptance Model

TPB: Theory of Planned Behaviour

TRA: Theory of Reasoned Action

TT: Turing Test

U: Usage

UTAUT: Unified Theory of Acceptance and Use of Technology

XML: Extensible Mark-up Language

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Introduction

The crescent demand for technological advances and products is pushing Artificial Intelligence to new levels. From Machine Learning to Natural Language Processing, we are watching a rapid transformation and we should be prepared to better understand how to take a competitive advantage out of it. In this sense, it is more important than ever to better understand how artificial intelligence can be helpful to us, both to improve our work and our quality of life.

In order to transform Artificial Intelligence into a competitive advantage to our work and our quotidian, it is important to understand how it is affecting the world around us and how we can take full advantage of this technological advent. Thus, it is crucial to understand how people accept technology, more precisely how people accept Artificial Intelligence and what can be done to lead people into adopting new Artificial Intelligence programs.

This study aims to understand if people are willing to accept Artificial Intelligence, by understanding previous studies of Technology Acceptance Theories and what Artificial Intelligence is. In this thesis, we create a new model based on the previous Technology Acceptance Theories, such as the Unified Theory of Acceptance and Use of Technology (UTAUT), to explain the acceptance of Artificial Intelligence and what influences the acceptance of Artificial Intelligence.

To achieve this goal, the work is divided into two main chapters to contextualize the problematic. The first one regarding Artificial Intelligence, what it is and how it has evolved. The second one regarding technology acceptance theories, the existing models and its evolution until the UTAUT and UTAUT2. After the contextualization, there is a methodology chapter, to explain how we developed the model and which techniques we used. Afterwards, there is a results chapter, where we present the results of the questionnaire and extract some practical information. The final chapter is where the main conclusions are drawn, limitations are identified and future research is suggested.

1. Artificial Intelligence

1.1. What is Artificial Intelligence?

In its very beginning, Artificial Intelligence (AI) was defined as the capacity of machines (such as computers, for example) to understand, learn and think just like human beings, which led to the possibility of simulating human intelligence through machines (Yunhe Pan, 2016).

This concept was first introduced in 1956 by John McCarthy, Marvin L. Minsky, Nathaniel Rochester and Claude E. Shannon (2006). In their proposal, the authors start by explaining that "*the study is to proceed on the basis of the conjecture that every aspect of learning or any other feature of intelligence can in principle be so precisely described that a machine can be made to simulate it*" (Mccarthy, Minsky, Rochester, & Shannon, 2006, p.12). Additionally, they identify various problematics of Artificial Intelligence such as: automatic computers, how to programme a computer to use a language, neuron nets, theory of the size of a calculation, self-improvement, abstractions and randomness and creativity.

However, some defend that Alan Turing (1950) was the foundation stone of Artificial Intelligence, because of the Turing Test (TT) that he presents in his 1950's article. The Turing Test is one of the most controversial and discussed topics of AI (Saygin, Cicekli, & Akman, 2000).

Nonetheless, Hayes and Ford (1995) disagree that the passing the TT should be assessed as the answer to the question "*Can machines think?*", they fail to see a practical purpose for the TT. In their opinion, AI should be much more than just a computer pretending to be a man imitating a woman. Artificial intelligence might be very different from human intelligence. The authors believe people should not focus in the wrong aspect of AI, the aim should be to reach a point where AI is useful to humans and not a point where AI can imitate the human intelligence. In their opinion, AI should be more a tool that humans can use to complete their tasks (Hayes & Ford, 1995) . In a similar way, Whitby (1996), recurred to comparable arguments as Hayes and Ford (1995), he went further by stating that "*the last thing needed by AI qua science is an operational definition of intelligence involving some sort of comparison with human beings*" (Whitby, 1996).

Just like Hayes and Ford (1995), Ken Goldberg in an interview with Frieda Klotz[1] shares his thoughts that people should not be frightened by the thought of machines replacing them, instead people should look at AI as an opportunity to improve their work, since it can simplify some tasks. Tasks that are repetitive can be done partially by the machine, giving more time for the employees to focus on more challenging and engaging tasks. Not only employees but also employers should foster the development of AI to support jobs and increase productivity instead of developing AI with the aim of replacing people with machines.

Nowadays, artificial intelligence is present everywhere, from our mobile phones to our televisions, even some fridges have artificial intelligence incorporated. These fridges facilitate the interaction with the user, allowing the user to know what is inside of the fridge without opening it as well as informing what should be bought based on what is normally in the fridge. It is even possible to write notes down, to play music or to organize the schedule for the whole family, and example of this is the Samsung fridge called family hub. As stated by Pan (2016), AI range of study has expanded, and now incorporates machine learning (such as chatbots, for instance), machine translation, game theory, pattern recognition, robotics, intelligent control and others. Pan (2016) also explains three setbacks of the development of AI naming a common factor: the inability of AI to adapt to modifications in the information environment.

[1] Available on MIT Sloan Management Review on: https://sloanreview.mit.edu/article/how-ai-can-amplify-human-competencies/

However, he also explains that the emergent stream of constant information, internet, other innovations and an increase in the general knowledge are promoting a development of AI.

1.2. Other important Concepts

1.2.1. Internet of Things (IoT)

With the recent technological developments, we have been pushed to an era where everything is online and connected through the internet. Our warehouses of data are online, our photos are online, our conversations with our friends are online, our games are online, even our life is online (at least what we decide to publish in our social networks).

On the one hand, this rises several threats, we lose privacy, we are more susceptible to have our identity stolen and our credit cards copied. But at the same time, there is constant innovation in cyber-security matters, allowing us to keep improving our connectivity without jeopardizing our privacy and our bank accounts.

On the other hand, this creates new horizon of opportunities to link everything and to create a better experience of the services companies can offer. As previously referred, nowadays we can have at home a fridge that interacts with us and creates shopping lists taking into consideration what is stored and what is not. Our smartphones will suggest us the fastest route to work without us telling it we are going to work, because they analyse our routines and know that every day at 7:00 in the morning we leave home and always go to the same place. The smart phone will assume this is our work and give us the fastest route, which can be very helpful in case there has been an accident, for example.

The IoT also facilitates the collection of data through the connectivity of our devices (computer, phones, car) which can be used to analyse patterns with more precision which can lead to better predictions and to better attend the user needs, enhancing the extent to which we can use Artificial Intelligence.

Additionally, the IoT also streamlines the gather of data which as pushed us to the concept that follows: Big Data (O 'Leary, Cox, & Ellsworth, 2013).

1.2.2. Big Data

According to O'Leary et al. (2013), there are several definitions for Big Data, having been nominated as Big Data by Cox and Ellsworth that called Big Data the usage of "*large of scientific data for visualisation*" (O 'leary et al., 2013, p.96). O'Leary et al. (2013) says that the definition of Big Data provided by IBM might be the most well-known one. In their words, they explain that *"big data could be characterized by any or all of three "V" words to investigate situations, events, and so on: volume, variety, and velocity*" (O 'Leary et al., 2013, p.96).

In their article, O'Learry et al. (2013) proceeds by explaining what each "*"V" words to investigate situations*" (O 'Leary et al., 2013, p.96) mean. Volume stands for the large amounts of data being created from various sources. Variety refers to the different and vast types of data that is generated, from structured data, such as databases, to unstructured data, for example publications in Facebook or LinkedIn. Velocity is related to how rapid this new information and data is generated and its goal is to understand what information we should gather and which one we can discard.

This massive amount of data needs to be stored, for then to be organized, treated and analysed. However, due to the dimension of the data, processing and extracting important information that is not available to everyone is not an easy task. The complexity of this task leads more and more people to use programs, such as PowerBI, that enable them to extract information from databases and use this information to gain a competitive advantage.

1.3. The evolution of the Turing Test and how it affected AI

To talk about the Turing Test is important to, first of all, explain this is a theory from 1950 and that it is an attempt to explain how we can understand if a machine can imitate a human, instead of understanding if machines think. For this, Turing (1950) introduces us the imitation game (IG).

The IG is played with a man (A), a woman (B) and an interrogator (C). The interrogator gender does not interfere with the game. C is in another room and knows the other players as X and Y, without knowing which one is A and which one is B. The goal is for C to correctly state the gender of X and Y. However, A will try to persuade C for him to make the wrong guess, while B will try to help C correctly identify both of them (Alan Turing, 1950).

After introducing the IG, Turing (1950) proceeds by saying that instead of asking the question "*Can machines think?*"(Saygin et al., 2000, p.468) we should instead ask "*Can machines play the imitation game in the place of A?*" (Saygin et al., 2000, p.468). So, instead of a man play as A, a machine will play in his place, according to Turing, it should be a digital computer. The purpose is for the machine to be able to imitate A in deceiving C for him to believe the "digital computer" is a woman. This because both A and B should try to convince C they are a woman.

Saygin et al. (2000) lists contrary views of the Turing Test and explains how Turing refutes them. One is the "*Gödel's Theorem which shows that in consistent logical systems of sufficient power, we can formulate statements that cannot be proved or disproved within the system*" (Saygin et al., 2000, p.470). However, Turing refutes this view by saying that he does not consider not making any mistakes a requirement for intelligence. Additionally, Saygin et al. (2000) explain that Turing states that "*although it is established that there are limitations to the powers of* *any particular machine, it has only been stated, without any sort of proof, that no such limitations apply to the human intellect*" (Saygin et al., 2000).

Another objection to the Turing thesis is the "*argument from consciousness*" (Saygin et al., 2000, p.470), that defends that for machines to have minds, they need to be conscious. This transport us to, on one extreme, the concept of solipsism, which would result that for us to know if machines think or not, we would need to be one. However, Turing refutes this view by explaining that if we assume everyone thinks, it would not be fair to assume that machines do not think.

Moor (1976) proposes that the Turing Test is a sufficient condition of intelligence-granting to computers, since it tests, directly or indirectly, almost all activities needed to identify that the computers think and since this is a severe test that is not easily completed. Nonetheless, Moor (1976) does not consider that this view is "*absolute*", as there might be other tests that might be proven more efficient.

Saygin et al. (2000) proceed by stating that Michie pointed out that human interactions are too complex for a computer to have encoded all the aspects that differentiate the way a human and a machine communicate. He gives the example of pronunciation, there is so many words and pronunciations that it would be virtually impossible to assess this. As if it was not enough the complexity, the conversation also takes place through an intermediary which means this would not be tested at all. Additionally, the authors mention that Michie points out the lack of emotional aspects of communication of machines that should also be incorporated (Saygin et al., 2000).

AI concept has evolved due to the discussion around Turing to its current definition. Nowadays, AI effort is to attribute human characteristics to machines, so that they can help humans with their work and daily life. The fast pace of the evolution of AI, has made some people raise awareness of the so called "*Singularity*", i.e. the point where the technology surpass humanity and takes control over humans. This concern is old and has been commercialized in the Film Industry, with films that show how humans can lose their independence and be surpassed by the machine, for instance in the movie "*I Robot*". In an interview with Klotz, Goldberg states that he does not believe that AI should be perceived as a threat but as a tool to facilitate and improve our quality of life and our productivity. Goldberg vision contrasts with Elon Musk and Stephen Hawking visions. While Stephen Hawking raises awareness to the "*Singularity*", Goldberg believes it is not humans against machines but humans with machines. Goldberg defends that we should abandon the idea of "*Singularity*" and move towards the idea of what he calls "*Multiplicity*". In his idea, humans should take full advantage from machines, in Goldberg words: "*This is elegantly summarized in a paradox posed by Hans Moravec 30 years ago: "Tasks that are hard for humans, like precision spot welding, are easy for robots, while tasks that are easy for humans, like clearing the dinner table, are very hard for robots.""*[2]. This statement perfectly supports the idea of Ken Goldberg, that machines should be seen as helpful instead of dangerous.

1.4. Machine Learning

Machine learning was born to pattern recognition, so that machines could learn without being programmed to execute the tasks but, instead, to learn from data. Machine learning is the concept of training computers with practical examples instead of programming[3]. While programming is very complex and is difficult to humans, giving practical examples comes at ease to humans, since we

[2] Quoted from his article on Davos 2015: The New Global Context available on: https://medium.com/davos-2015/lets-ditch-the-singularity-and-focus-on-multiplicity-3b397bc62449

[3] Adapted from SAS website: https://www.sas.com/en_ae/insights/analytics/machine-learning.html

do it on a daily basis, while conversing with our friends and narrating our stories of the day. Machine learning uses data in order to produce a model that can be helpful in performing tasks. Machine learning analyses sets of data, which should normally be pre-processed and then used to train the model.

Additionally, Big Data gives an edge to machine learning, since for it to be effective, it is important to have a large and diverse range of data. Big Data allows computers to have more examples to train, which lead to better and better results.

An example of machine learning application would be medical diagnosis. Through the data gather about the symptoms that are normally associated to each disease and recognizing patterns of what combination of symptoms are normally linked together for a certain disease can be a helpful tool to support medics with their diagnosis. For example, cough, fever and sneezing can be associated with a sore throat it can also be associated with a cold. Naturally, more data leads to more precise predictive models. Thus, if we have more data, the model will contemplate more symptoms to each disease and take into consideration the frequency of each symptom appearing, which should be more exacerbated in each case, leading to better and more precise medical diagnosis, resulting in a great support tool to medics.

However, without large and diverse data, the predictive models resulting from machine learning might be too blinded by their sample, i.e. the sample used to train the model might not be representative of the population in study. As a result, we should be very careful on what is beyond a Machine Learning model and how it was constructed so we can better use this technology.

1.4.1. Supervised learning

This type of learning is associated with classification and regression. Classification, is when through an input (data) we want a labelled output. Regression is when we have a continuous output. It needs the guidance of a data scientist to pre-process the data, choose the training sample and to test the model.

For this kind of learning to be effective it is important to pre-process the training set, cleaning the noise or incorrect labelled data in order for the training data not jeopardize the effectiveness of the model.

Some examples of supervised learning algorithms are logistic regression, naive bayes, random forest and artificial neural networks[4].

Additionally, and to test the precision of the model there should be used a sample test, ideally one sample that has not been used to train the model. We already know the results of the test sample, we just want to understand the precision of the model we created. The model will then predict the results of the sample test, and we can compare those predictions with the actual results. The reason why the training set and the test set should be different is to avoid overfitting. Overfitting happens when we use the same test and training sample, resulting in 100% correct precision because the results the model learned from are the same the model is being asked to predict. So, in order to properly test a model, it is important to divide data, before training the test our data, in order to use 70% as the train set and 30% as the test set, for example.

1.4.2. Unsupervised learning

Unsupervised learning, unlike supervised learning, aims to solve the problems without the assistance of humans. It is very complex for simple tasks but it is very helpful for the more demanding ones. Unsupervised learning analyses the common characteristics of the input to reach conclusions about clusters. Logically, one of the biggest applications of unsupervised learning is clustering (such as k-means clustering algorithm for example).

Some examples of unsupervised usage are exploratory analysis and dimensionality reduction. Exploratory analysis helps find structure in

[4] Adapted from: https://www.datascience.com/blog/supervised-and-unsupervised-machine-learning-algorithms

unstructured data, allowing people to arrange clusters more easily. One recurrent example of clustering is market segmentation. Dimensionality reduction aims to simplify data by deleting redundant features or information[5].

Table 1 summarizes the difference between supervised and unsupervised learning, namely regarding the types of variables and of analysis that can be performed for each one[6].

Table 1 - supervised learning vs unsupervised learning
Font: https://towardsdatascience.com/supervised-vs-unsupervised-learning-14f68e32ea8d

	Supervised learning	**Unsupervised learning**
Discrete	Classification	Clustering
Continuous	Regression	Dimensionality reduction

1.4.3. Deep learning

Deep learning is a subfield of machine learning that aims to mimic the way a human brain and all its neural networks work, so machines can be trained to solve more complex and abstract problems that normally would require people to make the assumptions and the thinking before recurring to the machine[7].

A neural network is composed of three or more layers, the input layer, that gathers the data that will learn from, the hidden layers where the data is processed and modified so it is easier to be analysed by the computer and the output layer, that gives us the result of the input. Deep learning refers to neural

[5] Adapted from: https://www.datascience.com/blog/supervised-and-unsupervised-machine-learning-algorithms
[6] Adapted from: https://towardsdatascience.com/supervised-vs-unsupervised-learning-14f68e32ea8d
[7] Adapted from MIT Technology Review article on https://www.technologyreview.com/s/513696/deep-learning/

network that have many hidden layers, that are making inferences through an iterative approach until a sufficient number of conditions is met, reaching a stopping point and resulting in the output, that then will be transmitted through the output layer. Deep learning uses a hierarchal neural network that uses both structured and unstructured data, in order to solve the problems. The number of hidden layer will be higher as the complexity of the problems increases (Hurwitz & Kirsch, 2018).

The recent developments of mathematical algorithms as well as with the increasing computational power has led deep learning to higher levels. Machines can, now, translate speech in real time with few errors. Deep learning capabilities are increasing every day since more data and more computational power are being generated daily.

1.5. Chatbots

"*The role machines play in communication process has changed rapidly in recent years*" (Mou & Xu, 2017, p.4), and chatbots are no exception. "*A chatbot system is a software program that interacts with users using natural language*" (Shawar & Atwell, 2007, p.29). Chatbots are a different form of Computer-mediated communication ("CMC") (Hill, Ford, & Farreras, 2015). To put it into another words, a chatbot is a specific type of AI that allows people to interact with a machine using the normal vocabulary they would use to communicate with another person.

Chatbots were originally idealized to mimic humans and, as a result, amuse other humans or beat the Turing Test, but with the pass of the time they have now a more important role. Shawar and Atwell (2007) explain how chatbots can be used to learn or practice a language, to retrieve information, to assist in e-Commerce, Business and other domains. An example of an e-Commerce chatbot is Julie, as per Figure 1, that is available on the website of Amtrak[8] to help the customer. Duolingo is a very well-known chatbot that allows people to learn and improve different idioms.

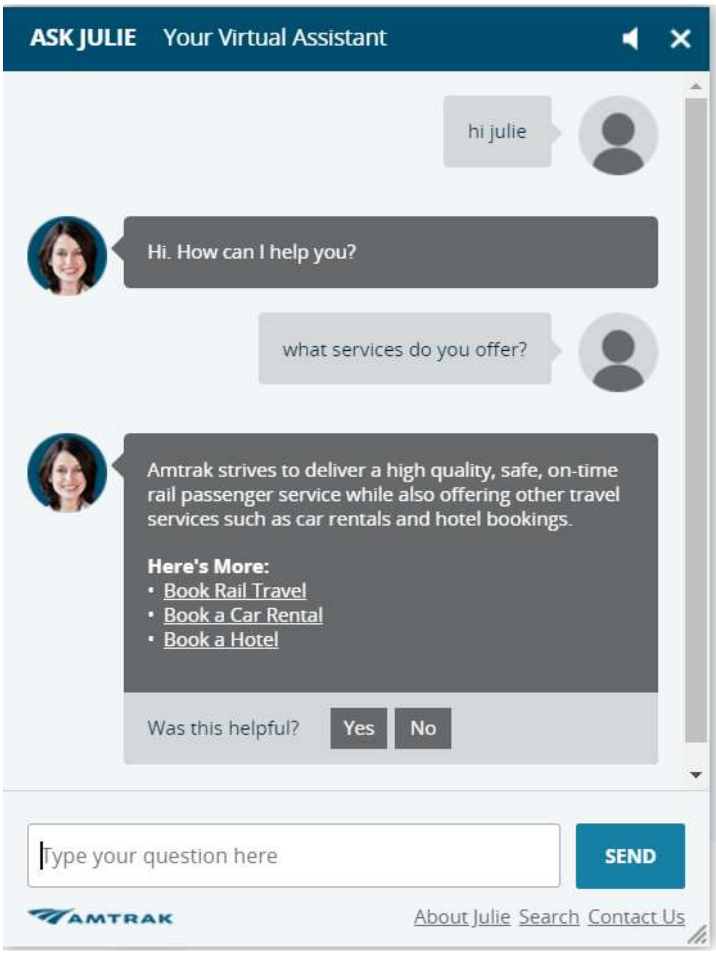

Figure 1 - sample of a conversation with a chatbot
Font: https://www.amtrak.com/home.html

Shawar and Atwell (2010) enumerate the different names people have given to chatbots ranging from virtual agents and dialogue systems to machine conversation language system. They continue by explaining that the main goal of a chatbot is to simulate the human-human interaction. In order to replicate this interaction, chatbots are equipped with language models and computational algorithms which allows the transformation of the information a user provides them, so the chatbot can generate a response and translate it to the same language

[8] Available on: https://www.amtrak.com/home.html

used by the user, allowing the user to understand what the chatbot is trying to say (Shawar & Atwell, 2010).

On 1966, Joseph Weizenbaum presented ELIZA, what is the most famous chatbot to exist before the internet, even though it is not the first one (Shah, Warwick, Vallverdú, & Wu, 2016). ELIZA was idealized to simulate to be a psychiatrist since this was a way for the chatbot to surpass its limitations and to justify giving vague answers and questions, such as "Tell me about boats" when confronted with the sentence "Tell me about boats" (Weizenbaum, 1966). As Weizenbaum (1966) explains that ELIZA looks for keyword in the sentences and, once it finds the keywords, it tries to process the information so it can answer the user. Weizenbaum (1966), presents five technical problems we should be aware of and try to solve: (1) identifying the right key word, (2) a minimal understanding of the context where the keyword is being used, (3) opting for the most appropriate transformation rule and the inherent transformation, (4) the development of a mechanism to allow ELIZA to answer "intelligently" without the presence of a keyword and (5) a provision of mechanisms that allow ELIZA to end a conversation. ELIZA opened the path to new chatbots to rise.

After some years, in 1995, ALICE (Artificial Linguistic Internet Computer Entity) came to life through Wallace. ALICE is based on AIML (Artificial Intelligence Mark-up Language) files, a derivate of the XML (Extensible Mark-up Language) files, place where the patterns about English conversation are stored. AIML can be deconstructed in AIML objects filled with data, that for their turn are divided into topics and categories. A topic is an optional attribute, that possesses a label and has many categories related to that same topic. Categories are rules for transforming input in output, consisting of a pattern that similarly to ELIZA matches a keyword of the input to the output and recurs to a template, to generate ALICE response (Shawar & Atwell, 2007).

ALICE has won three times the Loebner prize. The Loebner prize is an annual AI competition that recognizes the computer programs that are most human-like.

Another chatbot that has won a Loebner prize most recently and is well-recognized is Elbot. This chatbot was developed by Fred Roberts and has convinced 25% of the human juries that he was completely human-like. This was close to the threshold established by Turing for a machine to pass the Turing test, which is 30% (Deryugina, 2010). If anyone wants to talk with Elbot they can do it online[9].

While Shawar and Atwell (2007) start by presenting what a chatbot is, Mou and Xu (2017) start by pointing out that chatbots have a lack of awareness, explaining this lack of awareness will cause troubles in adaptation of chatbots to different situations, since people act differently depending on the context and on the situation. They call this the "personality paradox". Mischel and Shoda developed the cognitive-affective processing system (CAPS). CAPS would break down personality into cognitive-affective units (CAUs) that would reflect the core principles, moral values, beliefs and others of each individual (Mou & Xu, 2017). The purpose of this system is to allow chatbots to be able to effectively and coherently adapt to different situations.

Chatbots have several applications and many companies have started to develop chatbots as personal assistants (for example Google created Cortana and Apple created Siri), having been huge develops recently in this field. Google has developed his personal assistant to set up appointments and to order food, for example. However, chatbots are not limited to these tasks, they can be used in setting up work meetings, to facilitate communication between companies and clients, government and citizens. This can lead to a more efficient communication between agents, even though some aspects of communication might be lost. Conversations are not as rich as they would be as if people communicated with other people. However, the costs are drastically reduced and one robot can speak with many people at once, fastening the gathering of data and improving the

[9] Elbot is available to chat with anyone on: http://www.elbot.com/

time of services (Androutsopoulou, Karacapilidis, Loukis, & Charalabidis, 2018). Some companies have chatbots to assist people with difficulties they had ordering a product, booking a flight or with a general service, this chatbots serve as the first line to assist customers with their problems. Furthermore, people will be informed faster and will only recur to human contact if the chatbot cannot clarify their doubts, which in many cases are simple information that can be accessed easily if the right key word is typed.

2. Technology Acceptance

More than creating new technology, it is important to ensure that people will accept and use it. Otherwise our inventions will never become innovation and will not be useful. In order for technology to be of use and helpful, it is important to understand how it can be introduced in the daily routine, by convincing people that it will improve their quality of life. It is both important to understand how people, individually, accept the new technologies and also how it can be exploited and used by companies, for example by facilitating people's daily work. Additionally, it is interesting to understand how resistant people are to new technologies and what can be done to ensure a smoother transition.

Companies need to introduce technology to their working processes so they can win a competitive advantage towards their competitors. This is a complex and difficult process where all levels of employees need to align their working methods and accept the technology the company is trying to implement, by understanding it is helpful to everyone. So, at an organizational level, there is the necessity to focus on the individual level first, to convince all employees to adopt new technologies, by explaining it will facilitate their work, so they accept the technology and then the company can start taking full advantage of this new tool. Nonetheless, it is also very important to assure that the managers and supervisors also are supporters of the adoption of new technologies and that will challenge and incentive the employees and not the opposite.

Moreover, it is important that a company understands their motivations for adopting certain technology, explaining to the employees in detail where and how it can be helpful. For example, a company wanted to implement a system to control the time each employee worked daily, in order to better calculate the costs related to each project by understanding how much time each person spent on each process, which could result in better pricing, for instance. On the one hand, this could be perceived by the employees merely as a method of controlling when they are and when they are not working, how long are their breaks and how many hours they effectively work per week. On the other hand, this can be understood as a tool to understand when the employees prefer to work, if they normally arrive early and leave early or vice-versa. If the company shows to the employees that this can lead to more flexible schedules, this might increase the acceptance from the employees' side regarding this system. Another example would be using a robot to more repetitive and simple tasks. This would increase the productivity of the company because the employees would be able to focus on more complex and harder tasks, instead of being stuck with monotonous task.

Thus, the motivations for a company to adopt a new technology can be immense, from increasing profitability, to increasing the enthusiasm of employees, allowing them to focus on harder tasks by reducing the simple and repetitive ones. It is crucial that executives and managers promote the usage of technology, so the employees accept the new technologies and also to enable the companies they are responsible for to have more agility to answer to the clients demand (Zain, Rose, Abdullah, & Masrom, 2005).

In order to be able to understand what is the most evolved models regarding technology acceptance, it is first important to go through the most renowned existing models. We will be focusing essentially in organizational oriented technology accepted models, but we will finish with a consumer oriented one.

2.1. Theory of Reasoned Action

The Theory of Reasoned Action (TRA) was first presented to us by Ajzen and Fishbein in 1975, where they explain that behavioural intentions, that are the "antecedents" to any action or behaviour, are a way of emphasizing our beliefs and information that by performing a determinate action will lead to a specific output (see figure 2) (Madden, Ellen, & Ajzen, 1992). The subjective norm is the perception the individual has of the opinion of what his behaviour should be taking into account the specific situation (Schepers & Wetzels, 2007).

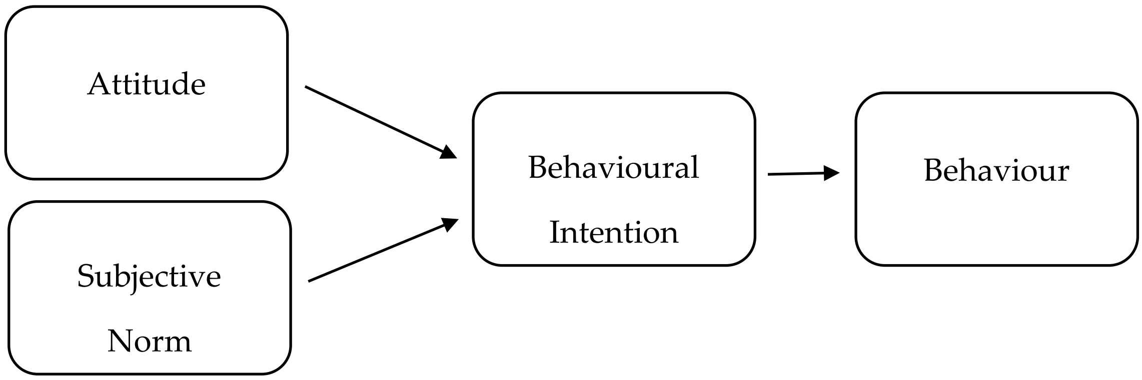

Figure 2 - Theory of Reasoned Action scheme (Adapted from: Madden, Ellen, & Ajzen, 1992)

2.2. Technology Acceptance Model

The Technology Acceptance Model (TAM) was inspired by the TRA and assumes that perceived usefulness (PU), as well as perceived ease of use (PEOU) strongly influence a person's attitude and behavioural intention to adopt a technology. TAM was initially idealized without the subjective norm, but since social psychologists know the environment influences individuals' decisions and behaviours, the subjective norm began to be part of the TAM. Nonetheless, there is still some controversy regarding the paper of the subjective norm since the empirical studies have been inconclusive (Schepers & Wetzels, 2007). As per

Schepers & Wetzels study in 2007, they assumed that the subjective norm not only influences the behavioural intention but also the perceived usefulness of a

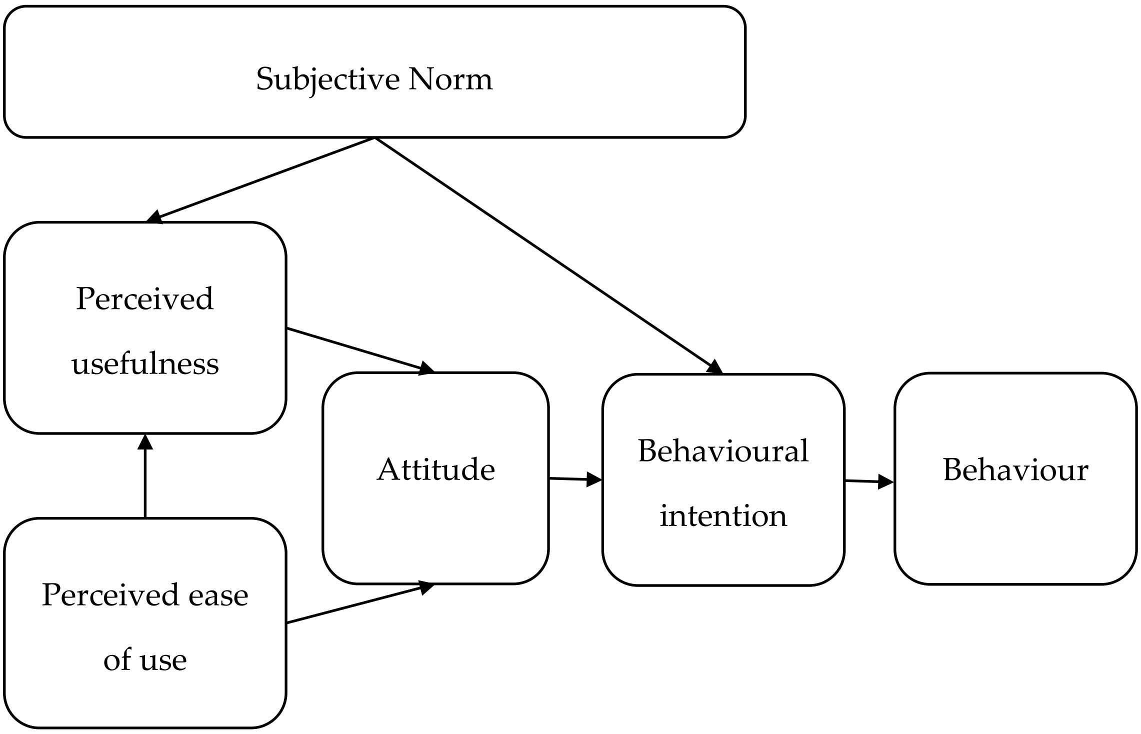

Figure 3 - Technology Acceptance Model scheme (Adapted from: Schepers & Wetzels, 2007)

technology which is the equivalent to the attitude in the TRA model (see figure 3).

2.3. Theory of Planned Behaviour

The Theory of Planned Behaviour (TPB) brings perceived behavioural control into TRA, giving a new input to create the output, i.e. the behaviour (see figure 4). Perceived behavioural control has both a direct and an indirect effect on the behaviour, which means that having a positive attitude and a subjective norm towards one specific behaviour, would under the TRA lead to the behavioural intention of performing that behaviour. Nonetheless, under the TPB the individual could have few information about the subject, resulting in a perceived of low behavioural control, which could lead the individual to not perform the behaviour that he would normally perform under the TRA (Madden et al., 1992).

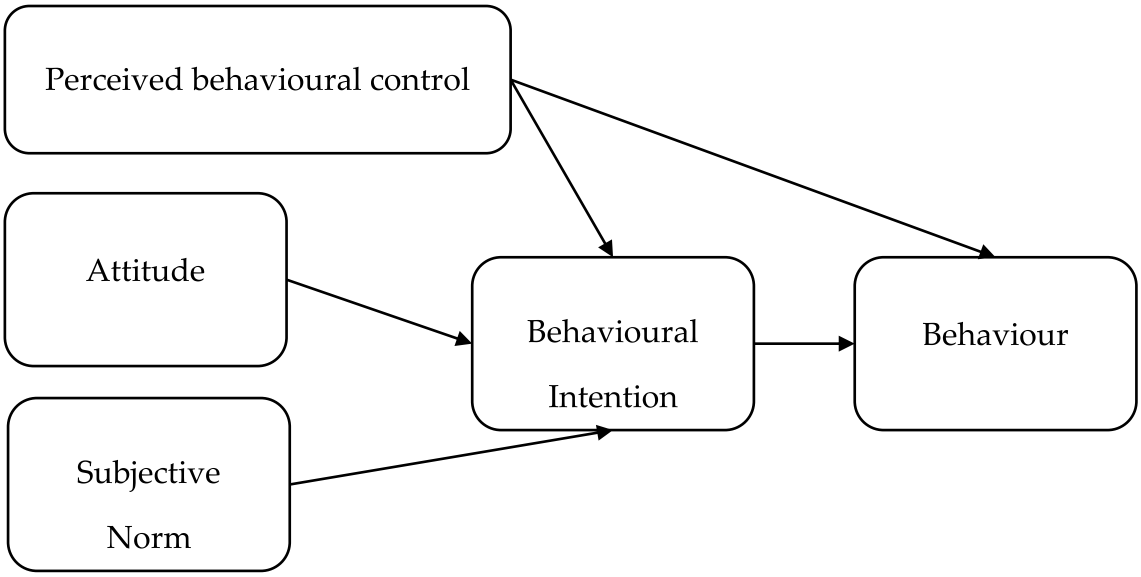

Figure 4 - Theory of Planned Behaviour scheme (Adapted from: Madden et al., 1992)

2.4. Model of Personal Computers Utilization (MPCU)

In this model Thompson, Higgins & Howell (1991) base their construction on the model of Triandis (Triandis in Thompson et al. 2006). Triandis explains the behaviour through facilitating conditions and intentions, and explains the intentions through social factors, affect and perceived consequences. On its turn, behaviour will influence habit hierarchies that will then influence affect, creating a circle as described in the image below. We can clearly see the influence of the previously mentioned models, and its evolution. This model is better represented in Figure 5. As we move forward, more and more constructs are added to the models, increasing models' complexity but enhancing the extent explained by the models.

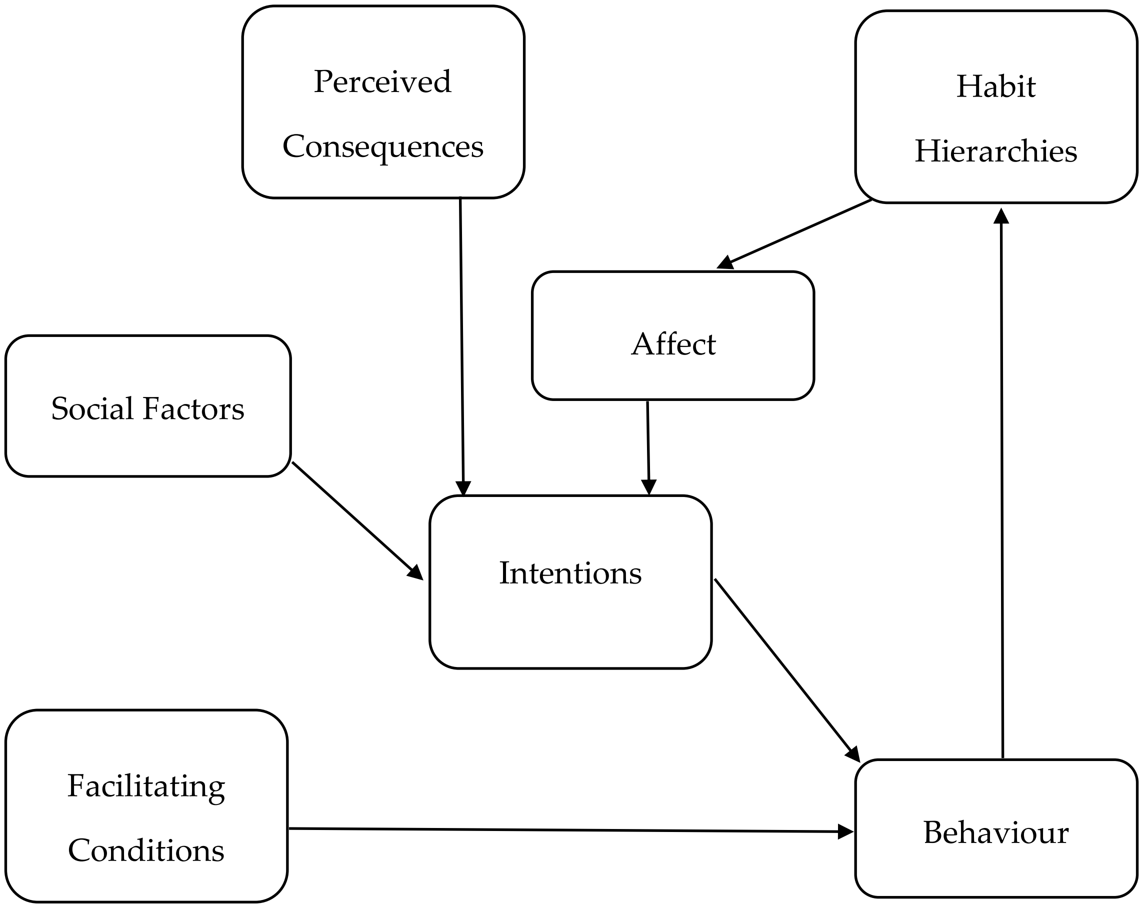

Figure 5 - Triandis scheme (Adapted from Thompson et al., 1991)

Thompson et al. (1991), taking into consideration the above scheme, tried to replicate what influences a person to use a computer. Their model attempts to explain the utilization of Personal Computers (PC) through the following constructs: facilitating conditions for PC use, social factors influencing PC use, affect towards PC use, complexity of PC use, job fit with PC use, long term consequences of PC use. (Thompson, Higgins, & Howell, 1991) Even though in this model we see clearly the influence of the Triandis (1971) scheme, the habit hierarchy somehow disappears and gives place to the social fit. In their paper, Thompson et al. (1991), explain how they break down each construct into questions or statements, in order to prepare a questionnaire and analyse the results under each construct (see table 2 below).

Table 2 - Explanation of the different Constructs of the PC utilization Model (Adapted from: Thompson et al., 1991)

Constructs explained

Social Factors

- The proportion of departmental co-workers who use a PC
- The management helps introducing PCs
- The direct supervisors are very supportive of PC use
- In general, the organization is supportive of the introduction of PCs

Affect

- PCs make work more interesting
- Working with a PC is fun
- PCs are okay for some jobs but are not for everyone

Complexity

- Using a PC takes too much time from the daily work
- Working with PCs is complicated and hard to accompany
- Using a PC involves a lot of mechanical operations
- The time to learn how to use a computer is too much

Job Fit

- How will the use of PC impact the job?
- Using a PC results in less time for more important tasks
- Using a PC can significantly improve the quality of the job
- Using a PC can enhance the efficiency of tasks
- Using a PC can lead to more output with the same level of effort
- Considering the tasks, to which extent does a PC helps for a job

Long-Term Consequences

- PC utilization increases the level of challenge of jobs
- PC utilization will increase the possibility to opt for job assignments in the future
- PC utilization allows a wider range of varieties for specific jobs
- PC utilization can lead to more meaningful work
- PC utilization can increase the flexibility of changing jobs
- PC utilization can give some opportunity to gain job security

Facilitating Conditions

- Guidance is provided to employees when choosing hardware and software
- There is someone available to provide software and hardware assistance if required
- There are specialized instructions regarding a specific software

Utilization

- The intensity of PC use in a job
- The frequency of PC use in a job
- The diversity of software used in a job

If we analyse the above table, we will quickly understand that, even if this model was originally intended to understand PC utilization, it can be easily adapted to try to understand the utilization of different technologies. Thus, it still is a very valuable model nowadays.

2.5. Motivational Model

In the same line of the PC utilization model, Motivational Model (MM) tries to explain the utilization of computers in the work, more precisely if "*people use computers at work more because they are useful or because they are enjoyable to use?*" (Davis, Bagozzi, & Warshaw, 1992, p.1111). Davis et al. (1992) explain that motivational theorists, normally divide motivation into two classes: extrinsic motivation – the individuals perform an activity in order to achieve valuable outcomes, for instance in order to be promoted or to receive a bonus payment; intrinsic motivation – individuals perform an activity without an obvious outcome. An example of extrinsic motivation is perceived usefulness and an example of intrinsic motivation is enjoyment, which are both presented in the analysis presented below and represented in Figure 6.

Davis et al. (1992) divide their work into 2 studies. In their first study, they had a sample of 200 students of an MBA program and they tried to understand the perceived usefulness, enjoyment, perceived ease of use, perceived output quality, usage intention and effective usage of a word-processing program (WriteOne) through a questionnaire. For the second study, their sample were 40 evening MBA students that were paid $25 to participate in a 2-hour laboratory session, where they used 2 computer programs: Chartmaster and Pendraw. While Chartmaster allowed users to create graphics that could be used to display business values in, for example, plot bars, Pendraw allowed users to draw virtual images on a tablet that would be visible as they were drawing. Participants used each program for one hour and half of the participants used Pendraw first and the other half used Chartmaster first. After using the programs, similarly to study 1, the participants answered a questionnaire in order to understand the perceived usefulness, enjoyment, perceived ease of use, perceived output quality, task importance, usage intention and effective usage of each program.

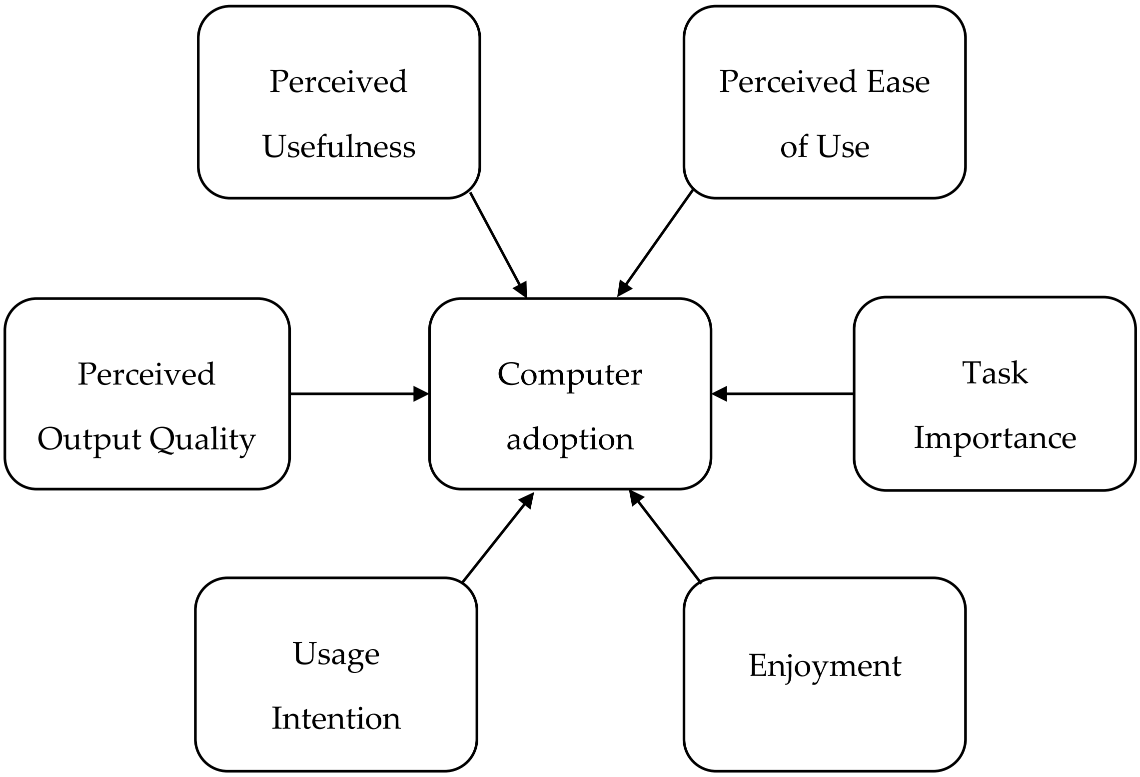

Figure 6 - Motivational Model scheme (Adapted from: Davis et al. 1992)

The results of their study were interesting, since both study 1 and study 2 gave similar results. According to the authors, perceived usefulness is the most important factor in adopting computers in the work place followed by how enjoyable the computers are to use. On one hand, Davis et al. (1992) say that making a program enjoyable might increase the acceptance of the same. On the other hand, they warn about the risk of turning programs enjoyable, since they might lead people to adopt programs that are not useful. This is interesting since videogames are enjoyable programs that can have little to no usefulness, which is in line with what Davis et al. (1992) are warning us about.

2.6. Decomposed Theory of Planned Behaviour (DTPB)

Taylor & Todd (1995) compared the TAM, the TPB and the decomposed TPB to try to understand which model better captured the usage of information technology. According to their study, the DTPB was the most effective model in assessing the behavioural intention. The DTPB assumes that the compatibility, ease of use and perceived usefulness influence the attitude that for its turn will influence the behavioural intention. Additionally, the peer influence and the superior's influence, influence the subjective norm that also influences the behavioural intention. Finally, the self efficacy, resource facilitating condition and technology facilitating conditions influence the perceived behavioural control that influences the behavioural intention and the usage behaviour. The usage behaviour is only influenced by the perceived behavioural control and by the behavioural intention.

The similarity with the TPB is clear, since the only difference is that instead of the attitude, the subjective norm and the perceived behavioural control being the beginning of the model, these are explained by other constructs as illustrated in the below Figure 7 (Taylor & Todd, 1995). This decomposition, results in a better comprehension of the different constructs which turns the model richer. However, according to Taylor and Todd (1995), TAM and both the pure and the decomposed TPB are comparable in terms of explaining information technology usage.

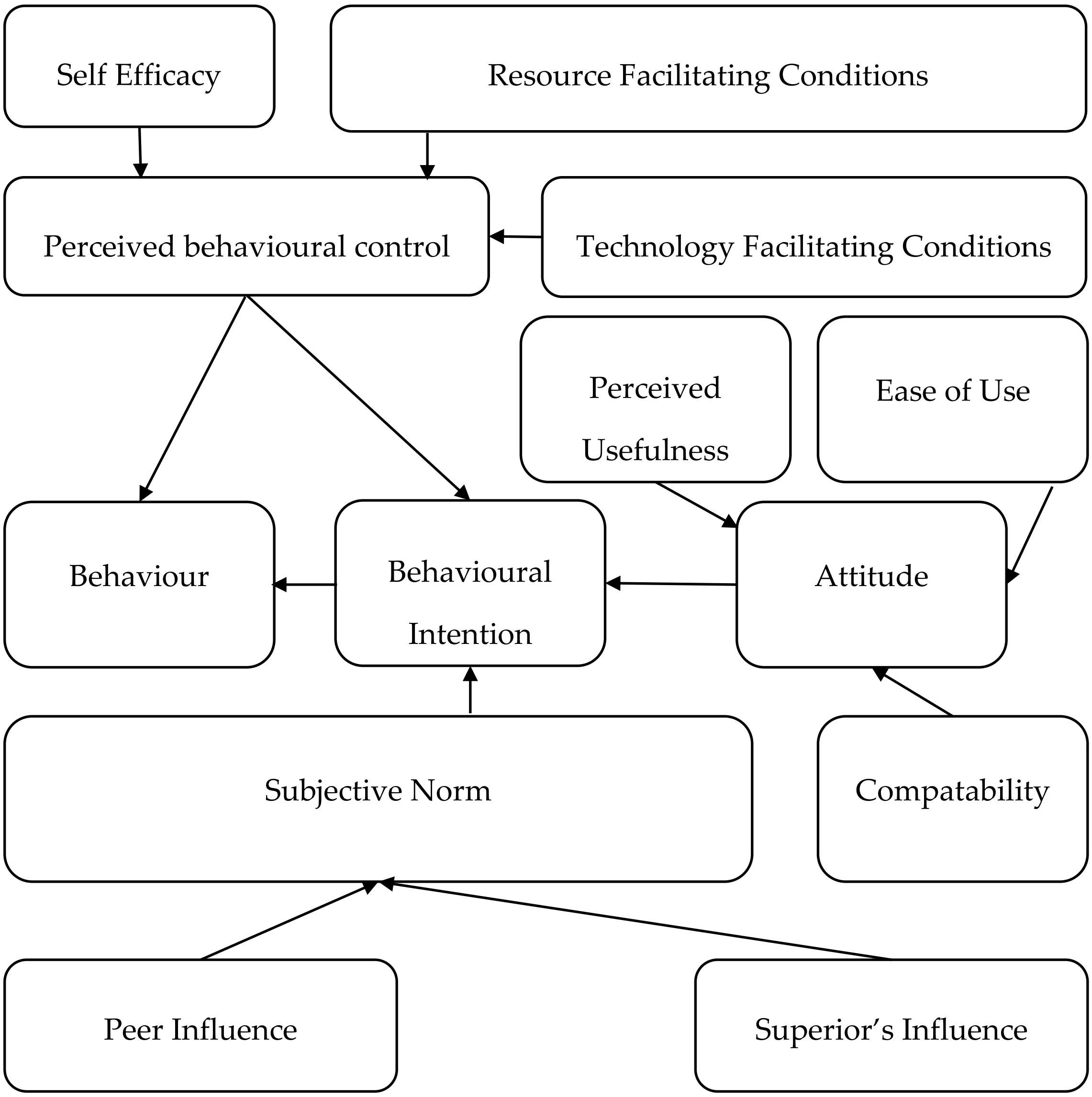

Figure 7 - Decomposed TPB scheme (Adapted from: Taylor & Todd, 1995)

2.7. Social Cognitive Theory

The Social Cognitive Theory (SCT) relates the so called cognitive factors with the affective factors and usage. It also assumes that the cognitive factors are computer self-efficacy, outcome expectations (performance and personal). For the affective factors comprehends affect and anxiety. The model tries to explain usage relating all the previously mentioned constructs (see Figure 8) (Compeau & Higgins, 1999).

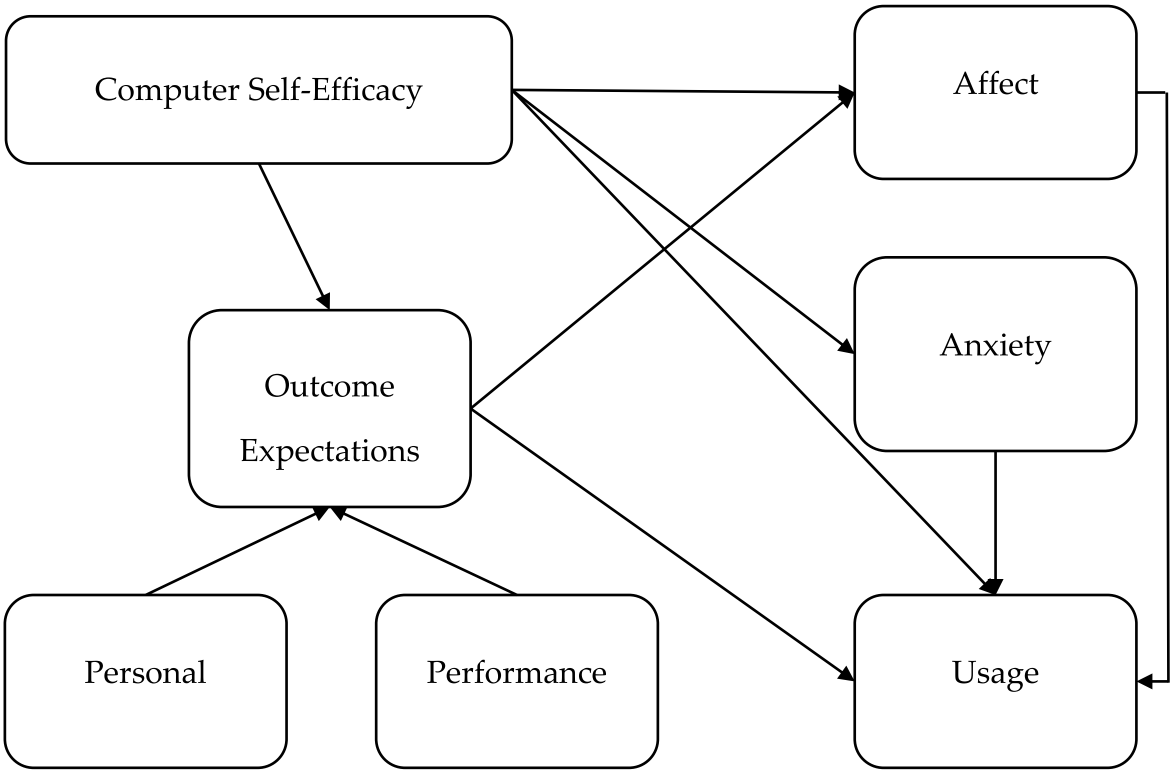

Figure 8 - Social Cognitive Theory scheme (Adapted from Compeau & Higgins, 1999)

According to the study performed by Compeau and Higgins (1999), the variance of usage is explained by the model in approximately 34% which is in line with the results of the previous studies from Davies et al. (1989) and Thompson et al. (1991), for example. According to Compeau and Higgins (1999, p.146), self-efficacy is "*defined as beliefs about one's ability to perform a specific behaviour – recognizing that our expectations of positive outcomes of a behaviour will be meaningless if we doubt our capability to successfully execute the behaviour in the first place*.". In their study, they corroborate the suspicious they previously mention, and that previous studies have also corroborate, that self-efficacy is a significant and strong predictor of the usage of computers. In this model, we see that all the constructs somehow evolve from the self-efficacy, which also explains the important role of this construct in this specific model.

2.8. Innovation Diffusion Theory (IDT)

The IDT, illustrated in Figure 9, intends to understand the acceptance and consequently usage of innovation by potential users. In this sense, the IDT focus on five significant innovation characteristics: relative advantage - the extent to which an idea (the innovation) enhances the existing ideas; compatibility – how the innovation is perceived by potential users, if it adds value and satisfies the needs it is intended to satisfy; complexity – the perceived difficulty and ease of use of the innovation by potential users; trialability – the extent to which the test of innovations is limited; observability – the extent to which the results of the innovation is noticeable to other people (Lee, Hsieh, & Hsu, 2011).

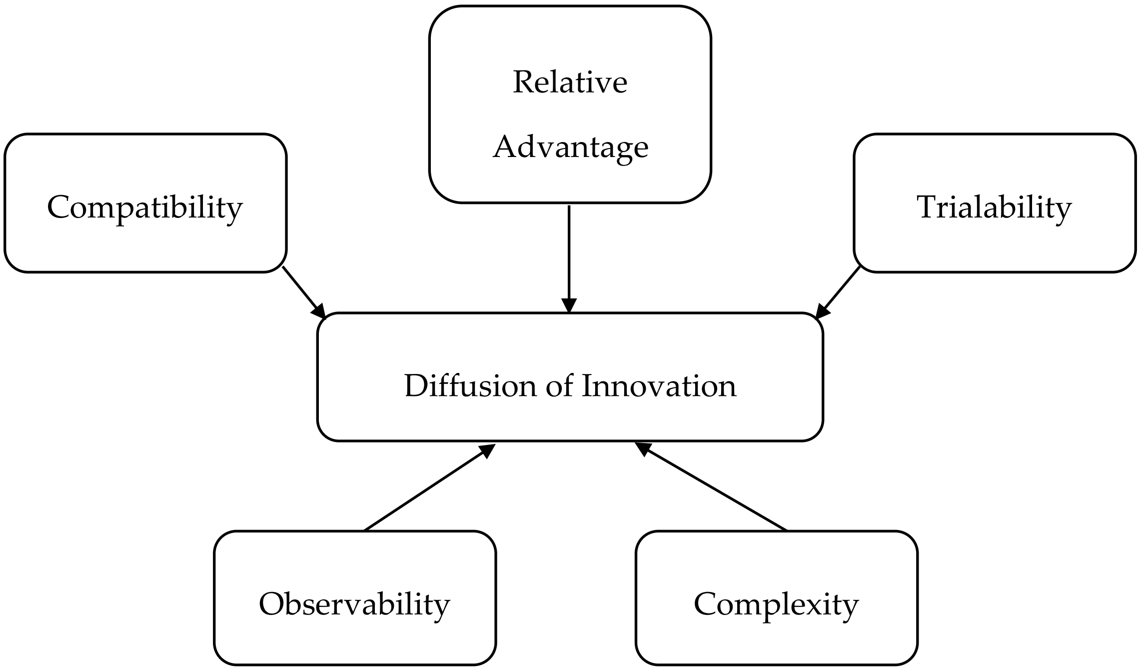

Figure 9 - Innovation Diffusion Theory scheme (Adapted from: Lee et al. 2011)

As previously mentioned in this study, the models previously mentioned all have common links which is also in accordance to what Lee et al. (2011) say. They compare the TAM with the IDT, they explain that the relative advantage is similar to the perceived usefulness and that the complexity is identical to the perceived ease of use. There are also similarities to other models since the compatibility is also present in the DTPB model as a construct that influences the attitude.

The hybrid model constructed by Lee et al. (2011) in order to study the behaviour intentions of individuals enrolling in e-learning programs, showed that compatibility and relative advantages had a positive significant impact on the perceived usefulness of e-learning programs. However, contrary to previous studies, complexity also had a positive impact on perceived usefulness of e-learning programs. This might be due to the content in study, since e-learnings aim to improve your knowledge and skills, its complexity can be perceived as a more demanding course that, even though it is more difficult, in the end will bring better results. Contrarily, in case the e-learning was simple, it can be perceived as not adding much value and, thus, as not being very useful. Regarding the perceived ease of use, as expected, was negatively impacted by complexity. They concluded that ease of use and usefulness were strongly linked, being both important factors to determine whether to adopt a technology or not.

2.9. UTAUT - Unified Theory of Acceptance and Use of Technology

Venkatesh et al. (2003) analysed and compared eight models: Theory of Reasoned action (1975), Technology Acceptance Model (1989), Theory of Planned Behaviour (1991), Model of PC Utilization (1991), Motivational Model (1992), Combined TAM (Theory of Acceptance Model) and TPB (Theory of Planned Behaviour) (1995), Social Cognitive Theory (1999) and Innovation Diffusion Theory (2001) (Chang, 2012). After this analysis they tried to compile the best features of each model into a new model, creating the Unified Theory of Acceptance and Use of Technology (UTAUT).

UTAUT can be divided into four aspects that influence the usage of technology: performance expectancy, effort expectancy, facilitating expectancy and social influence (see figure 10).

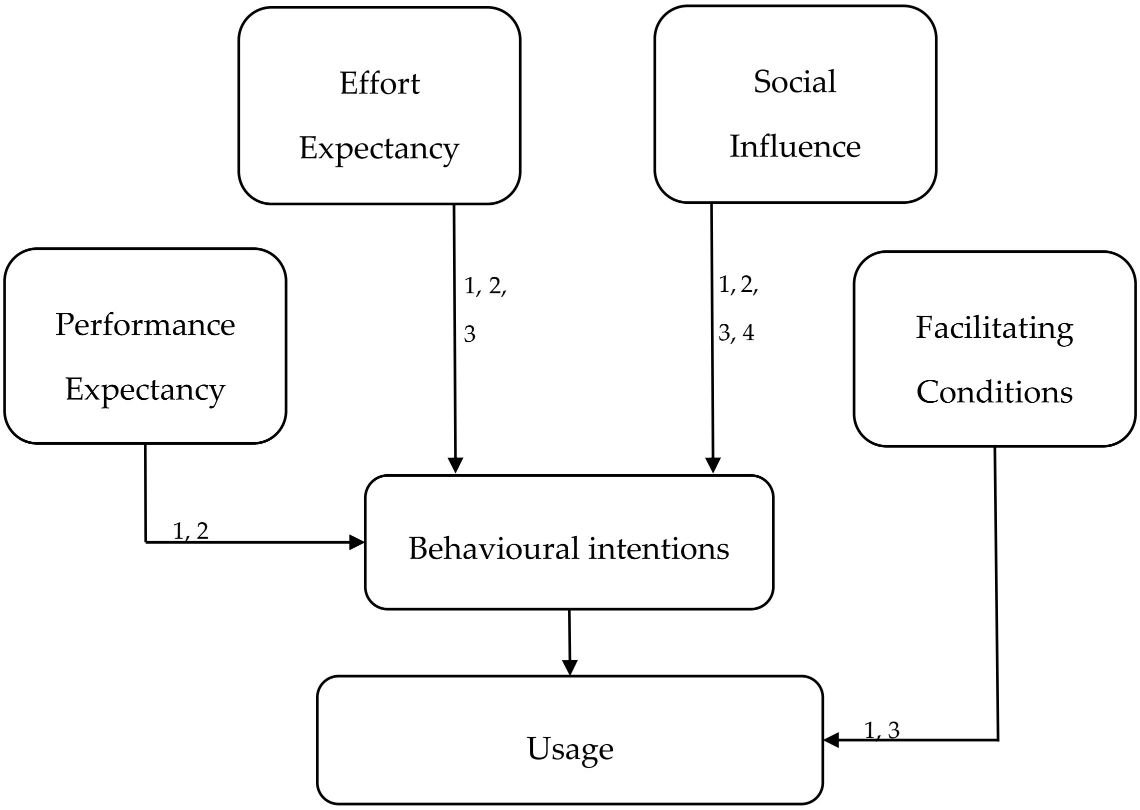

Figure 10 - UTAUT scheme (Adapted from: Venkatesh et al., 2003)
1 – age; 2 – gender; 3- experience; 4 - voluntariness

Performance expectancy is "*the degree to which an individual believes that using the system will help him or her to attain gains in job performance*" (Venkatesh, Morris, Davis, & Davis, 2003, p.447). This derives from perceived usefulness (TAM and MM), job-fit (MPCU), relative advantage (IDT) and outcome expectations (SCT). Venkatesh et al. (2003) hypothesized that performance expectancy influences behavioural intention considering the gender and age of the individuals.

Effort expectancy is "*the degree of ease associated with the use of the system*" (Venkatesh et al., 2003, p.450). This derives from perceived ease of use (TAM and MM), complexity (MPCU and IDT). Venkatesh et al. (2003) hypothesized that effort expectancy impacts behavioural intention considering gender, age and experience.

Social influence is "*the degree to which an individual perceives that important others believe he or she should use the new system*" (Venkatesh et al., 2003, p.451). This derives from subjective norm (TRA, TAM, TPB/DTPB and combined TAM and TPB), social factors (MPCU) and observability (IDT). Venkatesh et al. (2003) hypothesized that social influence effects behavioural intention considering gender, age, voluntariness and experience.

Facilitating conditions are "*the degree to which an individual believes that an organizational and technical infrastructure exists to support use of the system*" (Venkatesh et al., 2003, p.453). This derives from perceived behavioural control (TPB, DTPB and combined TAM and TPB), facilitating conditions (MPCU) and compatibility (IDT). Venkatesh et al. (2003) hypothesized that facilitating conditions influence usage considering the gender and experience of the individuals. Additionally, Venkatesh et al. (2003) also hypothesize that facilitating conditions will not have a significant impact on behavioural intention.

In the study performed by Venkatesh et al. (2003), the variance of behavioural intention is explained in 56%, while the variance of the technology use itself is explained by 40%, which is a substantial improvement when comparing to the previous mentioned models (Venkatesh, Thong, & Xu, 2012).

Nonetheless, the UTAUT has been updated to study the technology acceptance through a consumer optic, originating the UTAUT2. In this new model, Venkatesh et al. (2012) add three more constructs: hedonic motivation – relates to the enjoyment users get when using technology; price value – this relates to how affordable the technology is to consumers; experience and habit – while experience is based on the passage of time, habit relates to how a behaviour is automatic (Chang, 2012). This represented a significant improvement on the variance explained in both behavioural intention and technology use comparing to the results obtained by Venkatesh et al. (2003) regarding the UTAUT. In UTAUT2, the variance of behavioural intention is explained in 74% (56% in

UTAUT) and the variance of the technology use is explained in 52% (40% in UTAUT).

3. Methodology

There are two main paradigms characterizing research in the Information Systems field. On the one hand there is the Behavioural Science paradigm, that tries to develop and verify theories that attempt to explain and predict human behaviour in organizations. On the other hand, there is the Design Science paradigm that aims to create new artefacts that allow us to understand better human and organizational capabilities (Hevner, March, Park, & Ram, 2008).

The methodology adopted to develop this study was Design Science (DS) research. In this sense, it is important to first understand what design science research is all about. DS research tries to solve identified organizational problems through the creation and evaluation of artefacts (Peffers, Tuunanen, Rothenberger, & Chatterjee, 2008). According to Peffers et al. (2008), this can be achieved through seven steps: (1) the artefact should be created to analyse a problem; (2) the artefact should be relevant to solve an important business problem left unsolved until the moment; (3) the artefact "utility, quality and efficacy" should be rigorously assessed; (4) the research should be rigorous in the construction and evaluation of the artefact; (5) the research should relevant; (6) the development of the artefact should be based on previous studies; (7) the research must be properly communicated to the adequate audiences.

Bearing in mind the DS research process, studies regarding the acceptance of Artificial Intelligence have not been widely conducted. In this sense, this work aims to base their study on the existing theories of technology acceptance, adapting them to study the acceptance of Artificial Intelligence. Similarly to the technology acceptance models, this study will be based on a questionnaire that will divide the constructs into some questions.

Even though AI is a specific kind of technology, the constructs will remain pretty much the same as the used in the UTAUT and UTAUT2. Since these models already attempt to bring together the previous studies. We will be just adapting these models to understand the adoption of AI instead of technology in general. In this sense the main constructs that try to explain the behavioural intention to use AI and the usage of AI from a personal perspective: performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, habit and attitude. Additionally, we consider three moderating constructs: age, gender and academic background.

Before creating the questions for each construct, it is important to better understand each one of the constructs and how they are significant to this study. The questions to be included in the questionnaire per construct are schematized in Table 3.

3.1. Moderating variables

These moderating variables will help us cluster and understanding better how each specification, regarding gender, age and academic background, influence the relationships between the constructs and the intention behaviour and the adoption of Artificial Intelligence. This information will also be requested in the beginning of the questionnaire.

H0: In general, younger people will be prompter and more predisposed to use AI.

3.2. Performance expectancy

Performance expectancy is defined as the perception individuals have on how AI might help them performing their jobs better, through an organizational perspective. Through an education optic, performance expectancy can be defined as the perception individuals have on how AI can improve their study methods.

For this construct, the individuals will be asked to address the statements on a scale of 0 to 5, where 0 is completely disagree and 5 is completely agree. Upon analysis of the results, the scale will be break down in 3: individuals who answered with 0 and 1, will be deemed as resistant to AI; individuals who answered 2 and 3, will be deemed as receptive to AI; individuals who answered 4 and 5, will be deemed as AI enthusiasts.

H1: Academic background and age will be the biggest influencers, specifically people with management/economics or healthcare should have a positive performance expectancy regarding AI as well as the younger people.

3.3. Effort expectancy

Effort expectancy is defined as the perception individuals have on how difficult AI is to use, both on an organizational and on an educational level.

For this construct, the individuals will be asked to address the statements on a scale of 0 to 5, where 0 is completely disagree and 5 is completely agree. Upon analysis of the results, the scale will be break down in 3: individuals who answered with 0 and 1, will be deemed as resistant to AI; individuals who answered 2 and 3, will be deemed as receptive to AI; individuals who answered 4 and 5, will be deemed as AI enthusiasts.

H2: Academic background and age will be the biggest influencers, specifically people with engineering or mathematics background should have a positive effort expectancy towards AI as well as the younger people.

3.4. Social Influence

Social influence is defined as the perception individuals have on the expectations of other people towards the usage of AI, both on an organizational and on an educational level.

For this construct, the individuals will be asked to address the statements on a scale of 0 to 5, where 0 is completely disagree and 5 is completely agree. Upon analysis of the results, the scale will be break down in 3: individuals who answered with 0 and 1, will be deemed as not pressured to use AI; individuals who answered 2 and 3, will be deemed as moderately pressured to use AI; individuals who answered 4 and 5, will be deemed as highly pressured to use AI.

H3: Academic background, age and gender will be the influencers, specifically people with engineering, management/economics or mathematics background should have a positive Social influence towards AI. Younger people should also have this positive influence as well as men.

3.5. Facilitating conditions

Facilitating conditions are defined as the perception individuals have on organizations and/or schools have good infrastructures to support the usage of AI. This construct has more to do with the surrounding environment of individuals and how it is enabling and encouraging the usage of AI.

For this construct, the individuals will be asked to address the statements on a scale of 0 to 5, where 0 is completely disagree and 5 is completely agree. Upon analysis of the results, the scale will be break down in 3: individuals who answered with 0 and 1, will be considered to have poor infrastructures supporting the usage of AI; individuals who answered 2 and 3, will be considered to have sufficient infrastructures supporting the usage of AI; individuals who answered 4 and 5, will be considered to have good infrastructures supporting the usage of AI.

H4: Academic background and age will be the biggest influencers, specifically people with engineering background should have good facilitating conditions regarding AI, as well as people in their late 20's early 30's.

3.6. Hedonic motivation

Hedonic motivation is defined as the enjoyment people get from using AI. This might not have a big impact on an organizational level, since people are not there specifically to have fun. However, if we look from a consumer point of view this might be key into adopting new AI programs, such as augmented reality.

For this construct, the individuals will be asked to answer questions on a scale of 0 to 5, where 0 is not important at all and 5 is extremely important. Upon analysis of the results, the scale will be break down in 3: individuals who answered with 0 and 1, will be deemed as resistant to AI; individuals who answered 2 and 3, will be deemed as receptive to AI; individuals who answered 4 and 5, will be deemed as AI enthusiasts.

H5: Academic background and age will be the biggest influencers, specifically people who do not have an engineering background should have the need for a stronger hedonic motivation towards AI. Older people should require a stronger hedonic motivation to use Artificial Intelligence.

3.7. Price value

Price value is defined as the trade-off between price and utility of the AI program. This is one of the most self-explanatory construct, since no one will buy a very expensive AI program unless it is useful or if they have the monetary capabilities to buy it. This can also affect the organizations, but only at a managerial level, since they have to choose whether to adopt or not new AI innovations and it is crucial for them to understand if the money they pay for the innovation will improve the company performance.

For this construct, the individuals will be asked to address the statements on a scale of 0 to 5, where 0 is completely disagree and 5 is completely agree. Upon analysis of the results, the scale will be break down in 3: individuals who answered with 0 and 1, will be deemed as resistant to AI; individuals who answered 2 and 3, will be deemed as receptive to AI; individuals who answered 4 and 5, will be deemed as AI enthusiasts.

H6: Age and gender will be the biggest influencers, specifically younger people and men should be more flexible regarding the price value.

3.8. Habit

Habit is defined as the degree of exposure and recurrence to AI an individual is subject to. This is transversal in an organizational, educational and even personal level.

For this construct, the questions asked will be on a scale of 0 to 5, where 0 is never used AI and 5 use AI every day. Upon analysis of the results, the scale will be break down in 3: individuals who answered with 0 and 1, will be deemed as rarely users of AI; individuals who answered 2 and 3, will be deemed as occasional users of AI; individuals who answered 4 and 5, will be deemed regular users of AI.

H7: Academic background and gender will be the biggest influencers, specifically men and people with engineering, management/economics or mathematics background should have a higher habit to use AI.

Table 3 - Artificial Intelligence Acceptance constructions and questions/statements

Constructs and questions to be asked
Performance expectancy
PE1 Artificial intelligence programs greatly improve my performance. PE2 Using Artificial Intelligence programs allows me to have more time to focus on more demanding tasks. PE3 Artificial Intelligence allows me to perform the same tasks in less time. PE4 Artificial Intelligence automatized the more repetitive and monotonous tasks.
Effort expectancy
EE1 Using Artificial Intelligence programs is intuitive. EE2 Artificial Intelligence programs are easy to operate.
Social influence
SI1 My supervisors encourage me to use Artificial Intelligence programs. SI2 Everyone around me uses Artificial Intelligence programs. SI3 If I do not use Artificial Intelligence programs people will think I am not seizing my time to the maximum. SI4 My peers encourage me to use Artificial Intelligence programs.
Facilitating conditions
FC1 My workplace/school has easy access to Artificial Intelligence programs. FC2 Artificial Intelligence programs are widely diffused in the company I work for. FC3 Artificial Intelligence programs are widely diffused in the school I attend. FC4 There is available guidance to help me using the Artificial Intelligence programs.
Hedonic motivation
HM1 How important is to you enjoying using an Artificial Intelligence program? HM2 How important is the usefulness of an Artificial Intelligence program if you do not enjoy using it? HM3 How important is the enjoyment of an Artificial Intelligence program if it is not useful?
Price value
PV1 Even if an Artificial Intelligence program is useful, if it is expensive, it is not worth it. PV2 Artificial Intelligence programs are only useful when they are affordable. PV3 Artificial Intelligence programs should be more affordable.
Habit
H1 How regularly do you use Artificial Intelligence programs? H2 How often do you use 2 or more Artificial Intelligence programs in one day?
Usage
U1 I believe that Artificial Intelligence will have a positive influence on how we work. U2 I believe that Artificial Intelligence will improve our productivity. U3 I believe that Artificial Intelligence is a tool and not a threat to our jobs.

It is normal procedure to validate if our questions are well formulated and are not very repetitive by presenting our questionnaire to a random group of people and try to refine the questionnaire until everything is crystal clear. Another method to validate the pertinence of the questionnaire can be by recurring to experts in the field of technology acceptance theories. Nonetheless, due to lack of time, the questionnaire was only revised by five people. The results were positive and very few statements/questions suffered any alterations.

In this sense, the changes were the following: FC2 and FC3 merged, becoming only one question in order to avoid including in the questionnaire the option "Not applicable", now FC2 is: Artificial Intelligence programs are widely diffused in the company/school I work/study at.; PE4 is now: Artificial Intelligence automatizes the more repetitive and monotonous tasks.; A1 changed to: I believe that Artificial Intelligence has a positive influence on how we work.; and A2 is now: I believe that Artificial Intelligence improves my productivity.

The questionnaire[10] was shared through facebook, friends and the institutional e-mail of Universidade do Porto. 325 responses were gathered, but only 321 were considered since the remaining four were inconsistent. The questionnaire will be analysed in the next section.

For the analysis of the results, the programs used will be Microsof Excel, to pre-process the data and prepare a file to be read by R. R will be used to obtain some statistics and try to understand which variables are significant to explain the usage of Artificial Intelligence, by recurring to regression techniques. In principle, the results should be similar to the ones obtained with the UTAUT and UTAUT2.

[10] The questionnaire was available on https://forms.gle/VWS3R1g274EmYHfk9

4. Data Analysis

The questionnaire was responded by 321 people, from which 196 (60,7%) were females and 127 (39,3%) were males, as per figure 11.

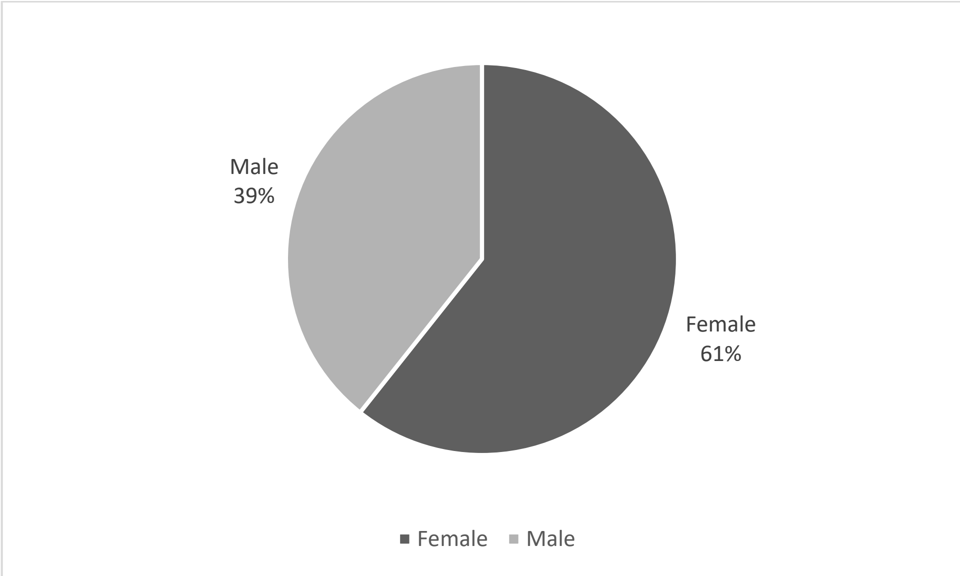

Figure 11 - Percentage of males and females that answered to the questionnaire

The distribution of the ages can be seen in Figure 12, where it is visible that the median (24) is lower than the average (29,45). Additionally, we can visualize that 50% of the responses are from people between the early 20's (22) and mid 30's (35).

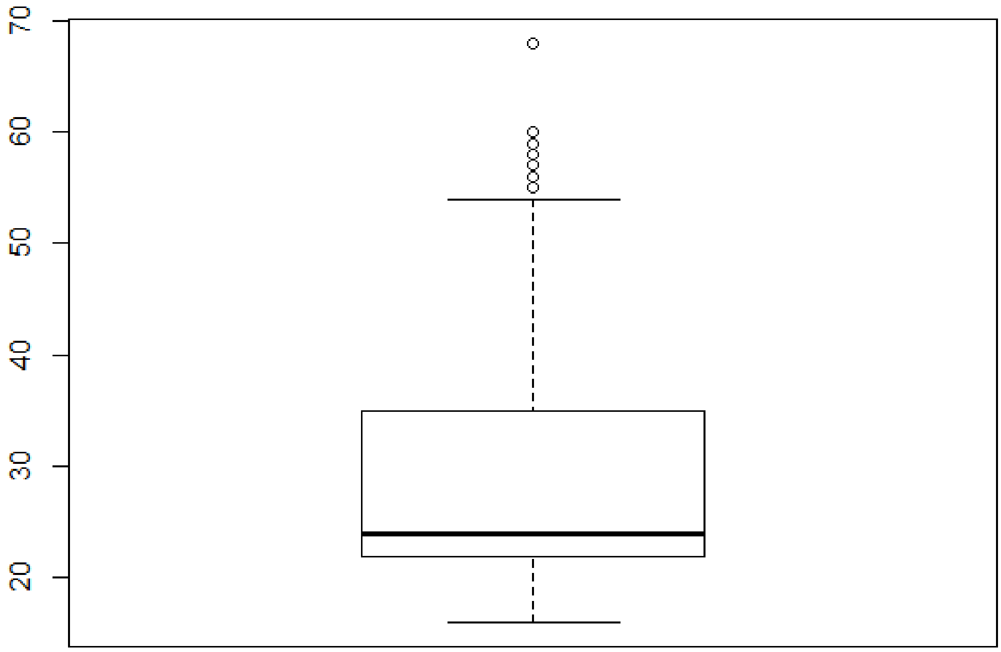

Figure 12 – Boxplot of ages distribution

The most represented background areas were: Healthcare (34,06%), Economics and Management (32,51%), Engineering (9,60%), Arts (7,74%), Scientifics Humanities (5,57%), Marketing and Advocacy (1,86% each) and Design, Science and Sports (1,24% each). The remaining ones were residual, representing merely 3,10% of the sample. All the information is visible in table 4 below.

Table 4 - Number of responses per area of specialization

Area of specialization	Number of responses	Percentage of the total
Healthcare	110	34,06%
Management / Economics	105	32,51%
Engineering	31	9,60%
Arts	25	7,74%
Scientific Humanities	18	5,57%
Marketing	6	1,86%
Law	6	1,86%
Design	4	1,24%
Science	4	1,24%
Sports	4	1,24%
Chemistry	2	0,62%
Information Technology	2	0,62%
Others	6	1,86%

After preparing the data for analysis, using excel, to eliminate missing values and incongruent observations, I created a CSV table to be read by R, in order to use a regression model to predict how the variables explained Usage. In the first regression models, all variables were used to explain the Usage of Artificial Intelligence. In this first model, only four variables were statistically significant, being them performance expectancy (PE), effort expectancy (EE), price value (PV) and habit (H) and the squared error (R^2) was of 60,73%, which meant that the usage (U) was explained 60,73% by the model. However, there were some variables that were not statistically significant. In this sense, we followeda general to specific strategy to search for an appropriate model. First, by eliminating manually the variables that were not significant and, secondly, using the Akaike Information Criterion (AIC) as a guiding principle. With the second strategy, we selected our model, a reduced model that, even though it had a lower R^2 (56,72%), all the variables were statistically significant, being them PE, EE, PV, H, social influence (SI) and gender (G).

This allowed us to choose our second model as being the fittest, since the first had multiple variables that were not significant and if we removed the non-significant variables, we would reach a model with a smaller R^2 than the model where all the six variables were significant (see Model 2 in the Figure 13 below).

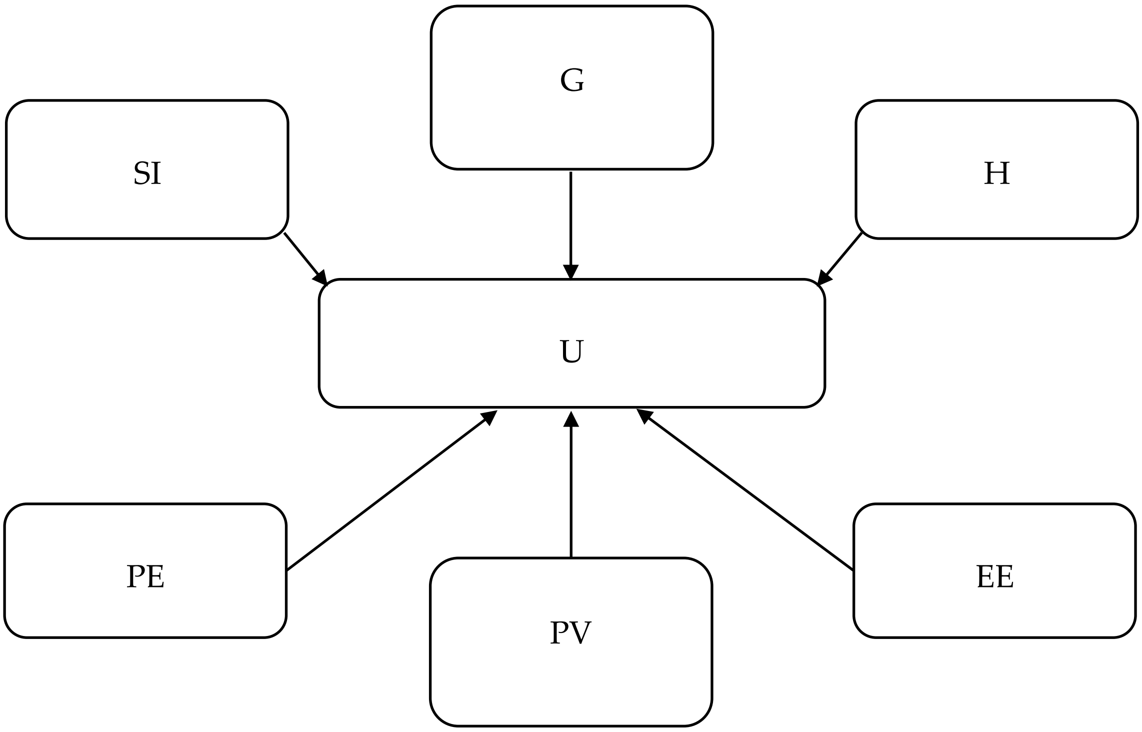

Figure 13 – Artificial Intelligence Acceptance scheme
(SI – Social Influence; G – Gender; H – Habit; EE – Effort Expectancy; PV – Price Value; PE – Performance Expectancy; U – Usage of Artificial Intelligence)

Additionally, all the assumptions for a statistical model to be valuable, were verified, namely the heteroscedasticity, multicollinearity and normality. In order to deal with the presence of heteroscedasticity, we used the method of the robust standard errors, which did not alter the results of the regression. The only red flag was the correlation between PE and EE, which is not counter-intuitive, since the if we expect a good performance, in principle we also expect that the effort we must put into the program will not be very high when comparing to the effort we were already incurring in without the AI program. Otherwise, the performance will not be increasing as much as anticipated. The sample did not follow a normal distribution. However, since we had a large database we proceed with the analysis.

Regarding the analysis of Model 2 (Table 5) itself, it is important to analyse the p-value of the F test of this model. The p-value of this model is very close to zero, which testifies the statistical significance of the model and the importance of the explanatory variables in explaining the usage of AI. All the explanatory variables positively influence the usage of AI and typically it is more likely a higher usage of AI by males when comparing to the reference type, females.

Table 5 - Model 2 of regression regarding Artificial Intelligence Acceptance
Significance Codes: "." 0,1 ; "" 0,05 ; "**" 0,01 ; "***" 0,001*

	Model 2 - AIA			
	Estimate	**Std. error**	**t**	**p-value**
(Intercept)	0,07044	0,12951	0,544	0,58688
Gender Male (reference: Female)	0,08587	0,04880	1,760	0,07944 .
Performance Expectancy	0,56079	0,04621	12,137	< 2e-16 ***
Effort Expectancy	0,10119	0,04855	2,084	0,03794 *
Social Influence	0,11810	0,04601	2,567	0,01072 *
Price Value	0,09811	0,04480	2,190	0,02925 *
Habit	0,12074	0,03876	3,115	0,00201 *
R^2	56,72%			

Additionally, the variables age, background, hedonic motivation and facilitating conditions did not play a representative role in explaining the usage of Artificial Intelligence, which lead to their exclusion from the predictive models.

When comparing this model with the UTAUT2, the results are very similar and the percentage of usage of Artificial Intelligence explained by this model is 56,72%, a bit higher than the 52% of the results of UTAUT2. Nonetheless, we must keep in mind that this model is studying only a specific type of technologies whereas the UTAUT2 studies the acceptance of all kinds of technology.

It is also important to bring out that the big majority of the sample uses technology frequently, since people responded very positively to the amount of times they use this technology. If we look to the three levels usage has where 1 is rarely use, 2 is use sometimes and 3 is use regularly, the mean of the responses was 2,445, meaning that almost all the people that responded to the questionnaire tends to use Artificial Intelligence quite regularly.

4.1. Hypothesis 0

The null hypothesis predicted that younger people would be more prompt to adopt Artificial Intelligence technologies than older people.

This turned out to not be proved by our study, since age is not included in our final model, due to the lack of relevance.

As per the Figure 14 below, we understand that there is no tendency and that the average usage of Artificial Intelligence does not depend on age.

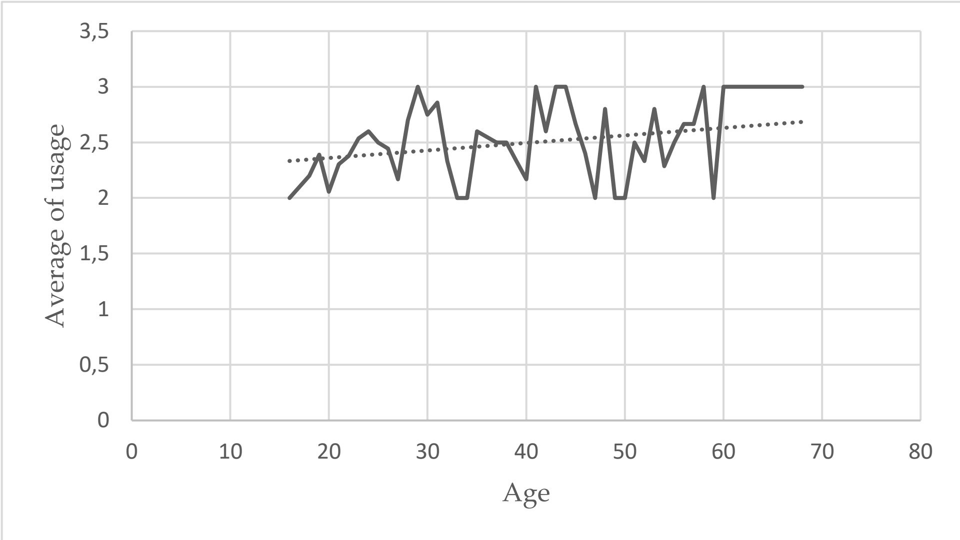

Table 6– Age and AI usage distribution

4.2. Hypothesis 1

Regarding the hypothesis one, we already understand with the null hypothesis that age is not a relevant factor for AI usage, it is now interesting to understand if background can play a more relevant role. According to our model, background should, like age, not play an important role in AI technologies acceptance and usage.

By analysing the below Figure 15, it seems that Nutrition, no specialization, Information Technology, Entrepreneurship, Architecture and Accounting are very prompt to use AI. However, we have to keep in mind that these backgrounds have a very reduced sample, corresponding to just one observation, apart from Information Technology, that corresponds to two observations. Thus, no relevant conclusions can be drawn from the study regarding academic background and the impact it has on AI usage. The hypothesis one, just like the null hypothesis was not proven to be true.

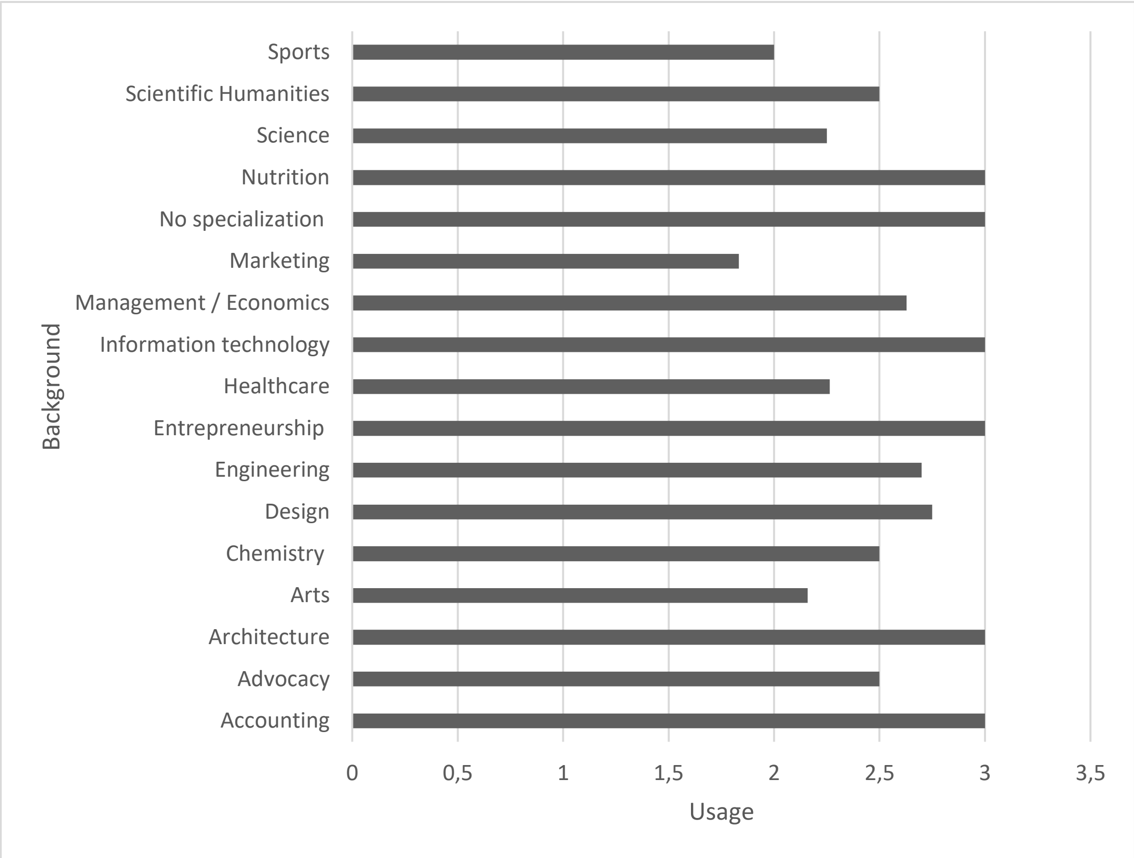

Figure 15 – Background and AI usage distribution

4.3. Hypothesis 2, 4 and 5

Since these hypothesis assumed that hypothesis 0 and 1 were correct, this one is also invalid since age and background do not play an important role in defining the usage of Artificial Intelligence.

4.4. Hypothesis 3

This hypothesis was partially correct, since gender was the only variable of the moderating variables that was statistically significant in our model. In this sense, males are more prompt to adopt Artificial Intelligence technologies than females, which is in line with the last part of the third hypothesis and can be seen in Figure 16. Nonetheless, age and background turned out to be poor predictors of how a person views AI usage.

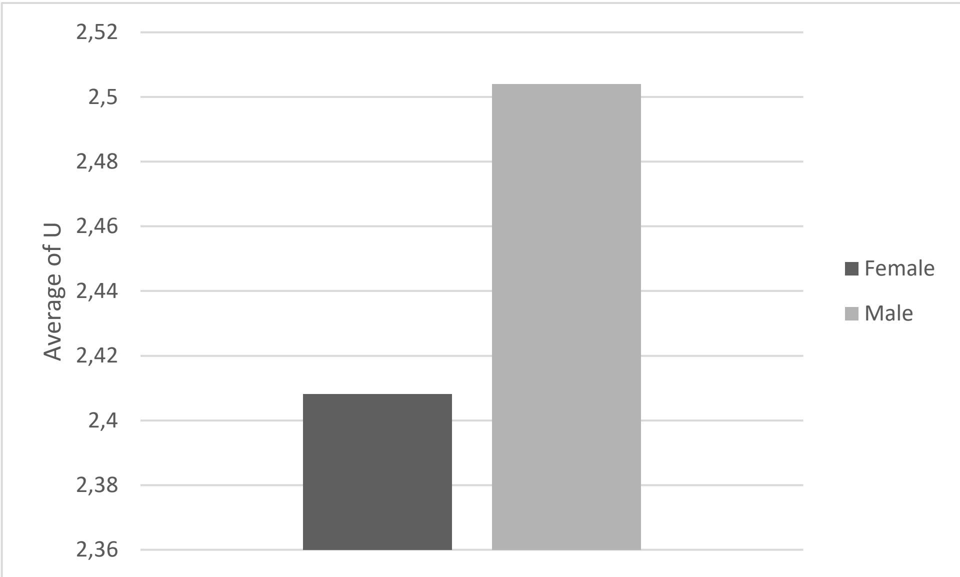

Figure 16 - Gender and average of AI usage

4.5. Hypothesis 6

Just like in usage of AI, gender positively influences the price value, and males are slightly more flexible regarding the price value than females, as can be seen in Figure 17. This is accordingly to hypothesis 6.

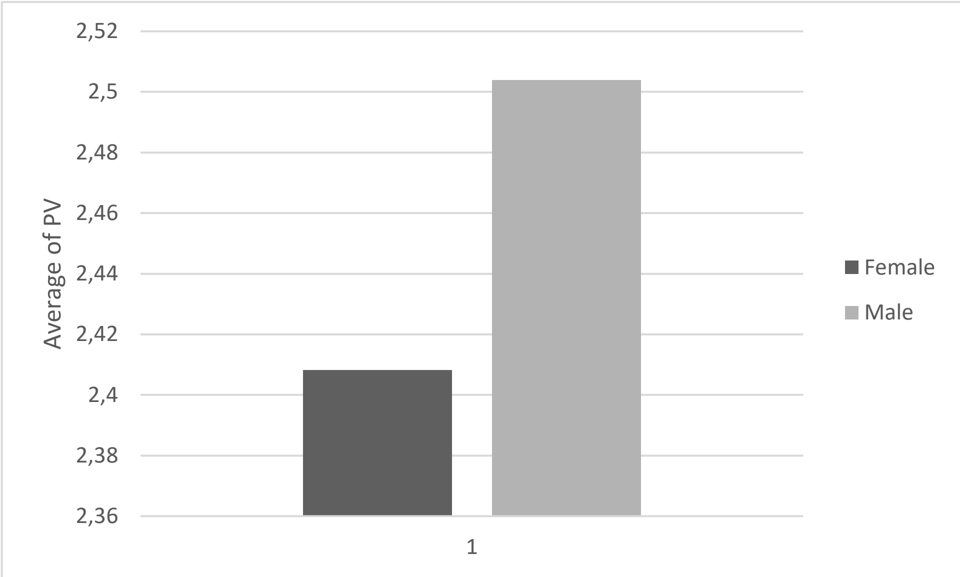

Figure 17 - Gender and average of Price value

4.6. Hypothesis 7

This hypothesis is in line with the previous one and also assumes that gender, specifically men, will have a positive influence in the variable habit. Similarly to the two previous figures, we can see that males also have a higher value in the variable habit than females in Figure 18.

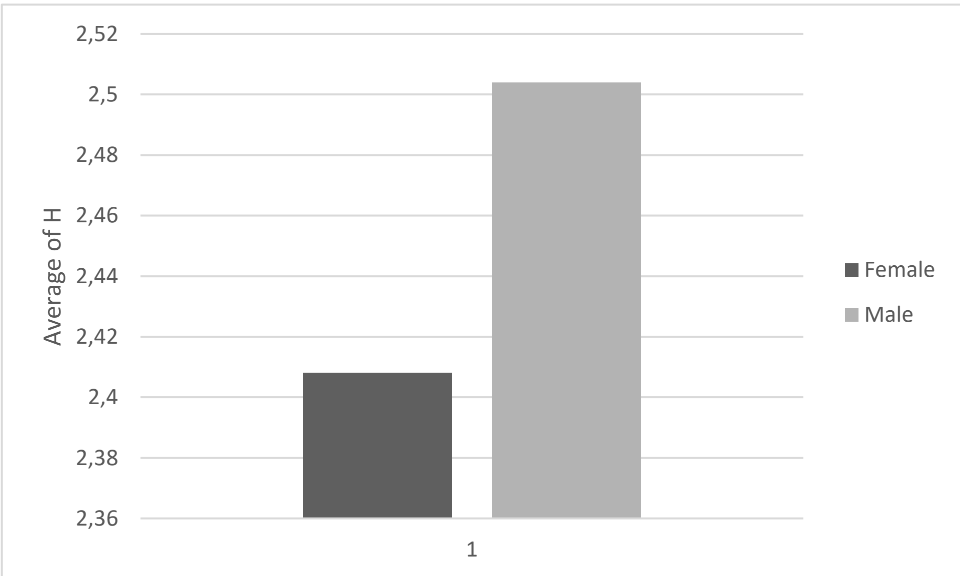

Figure 18 – Gender and average of habit

Conclusions

Throughout this study, we analyze the different areas of Artificial Intelligence, such as chatbots and machine learning, and try to understand if people adopt Artificial Intelligence programs as well as the main factors that lead people to adopt this technology.

Through the model developed during this thesis, we understand that people are willing to use Artificial Intelligence and that, in fact, people are already using Artificial Intelligence programs to some extent.

The main aspects of our model, that aims to explain the factors that influence the usage of Artificial Intelligence, are:

a) The generality of people already uses Artificial Intelligence programs;
b) The usage of Artificial Intelligence programs is strongly affected by the perceived performance, people tend to be more prone to use AI programs if they think it will increase their performance;
c) The facilitating conditions are not relevant to determine the usage of AI programs, contrarily to what might have been expected. People do not find that having all the conditions will lead them to use AI;
d) People strongly associate the usage with performance, to the point that if a program is enjoyable but not useful, people will rather not use it;
e) Taking into consideration the results, the preferable method for employers and managers to instigate the usage of Artificial Intelligence programs in their work is by explaining and exemplifying how this can lead to an increase of the performance of the employees without increasing the effort employees need to put into their jobs;
f) They can also explain that everyone is using Artificial Intelligence and that it is a valuable tool, but at the end of the day, the biggest influencer is the performance expectancy versus the effort expectancy. Since people want

to be more efficient, by doing better job without put a lot more effort or, in extreme cases, with less effort than before.

This study aimed to be innovative, by giving a twist to the existing technology acceptance theories and paving a new road for acceptance of Artificial Intelligence theories to be developed.

Throughout this thesis many types of Artificial Intelligence were mentioned and all of them are in constant development, which leaves plenty of room left to improve theories of technology acceptance, since it probably will be more efficient to focus in one specific kind of technology and try to understand what leads people to adopt those kinds of technology. This was precisely what we aim to do during this thesis, focusing on Artificial Intelligence and the model we constructed, being very similar to the UTAUT2, had a slightly higher R^2. This leads to the possibility that studying chatbots acceptance alone, for example, would lead to better results since we could understand better which factor influence that specific technology.

This study had one major limitation that was time constraint, since I have been working while developing this project. This also resulted in the questionnaire only being online for 8 days, which might have reduced the sample.

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