UNIVERSITÀ POLITECNICA DELLE MARCHE
FACOLTÀ DI ECONOMIA "GIORGIO FUÀ"

Corso di Laurea Magistrale in
International Economics and Commerce

Artificial Intelligence and voice commerce in marketing: an experiment with Amazon Alexa

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Anno Accademico 2019 - 2020

ABSTRACT (Italian Language)

Negli ultimi anni il campo di azione dell'Intelligenza Artificiale (IA) si è sviluppato a ritmo serrato con l'applicazione di "software intelligenti" in diversi settori. Tra questi, il marketing rappresenta uno di quelli nel quale l'applicazione di tali tecnologie può apportare i maggiori benefici grazie soprattutto alla loro capacità di raccogliere ed elaborare una grande quantità di dati relativi al cliente.

Di recente, nell'ambito dell'intelligenza artificial e nel marketing, si è affermato un nuovo trend: l'utilizzo sempre maggiore degli assistenti vocali e, di conseguenza, del voice commerce. Rientrano in questa categoria tutte le diverse attività che vengono svolte per completare un ordine attraverso un assistente vocale. In questo contesto, gli assistenti vocali possono essere visti come strumenti che supportano il processo di acquisto del consumatore, fornendogli raccomandazioni e offerte personalizzate sulla base delle proprie caratteristiche e preferenze.

Nonostante le grandi opportunità di sviluppo offerte da questa nuova tecnologia, non sono presenti molte ricerche in letteratura volte ad analizzare l'impatto dirompente degli assistenti vocali nel contesto del marketing.

In particolare il presente studio ha l'obiettivo di esplorare come gli assistenti vocali, dotati di intelligenza artificiale, possano di fatto cambiare il comportamento d'acquisto dei consumatori.

A tal fine si è deciso di analizzare il ruolo della fiducia dei consumatori nella scelta di un'opzione di default quando essa coincide con la private label associata all'assistente vocale, e come questa scelta influenzi la soddisfazione del cliente.

Quest'ultima domanda di ricerca è stata studiata sperimentalmente, andando ad emulare un vero e proprio acquisto utilitario tramite una ricerca ad ampia corrispondenza (n=60).

I risultati hanno mostrato come le imprese e i brand siano particolarmente minacciati dalle private label nel commercio vocale. Pertanto, questi dovrebbero pianificare attentamente come sviluppare e stabilire la loro presenza sulla piattaforma.

ABSTRACT

Recently Artificial Intelligence (AI) is developing at a fast pace and it is applied to many areas. Among them, marketing is expected to derive the most promising value impact from AI, due to the high level of data that is possible to obtain from the customers' interaction with the companies.

Recently, artificial intelligence in marketing is witnessing the emergence of a new trend: consumers are increasingly buying voice assistants (VAs). In particular, users are starting to place orders through these devices. The series of activities carried out to complete an order through a voice assistant goes under the label of "voice commerce". Voice assistants, like Amazon Alexa, can be defined as tools that support the consumer's decision process, providing recommendations trying to match products to consumer's needs.

Despite the great opportunity provided by voice commerce for brands and consumers, studies addressing the disruptive impact of voice assistants on the marketing practice are very rare.

Consequently, this research aimed at investigating artificial intelligence in the context of voice commerce, in order to analyze how this new technology will influence the consumers' buying behavior.

In particular, it was studied the role of consumers' trust in the selection of a default private label option, and its implications for decision satisfaction. To test this effect, an experimental study was designed simulating an actual utilitarian purchase with a broad search match (n=60).

The results showed that brands others than private labels are those more challenged by voice commerce. Therefore, they should plan carefully how to develop and establish their presence on the platform.

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INTRODUCTION

Recent years have witnessed a renewed interest in Artificial Intelligence (AI) among both managers and academics, mainly due to the great progress achieved in this field, thanks to the greater availability of Big Data, the emerging IoT (Internet of Things) systems, and the improvements in computing power.

AI is increasingly considered an unprecedented revolutionary technology with the potential to transform humanity (Brock & von Wangenheim, 2019). The theoretical physicist Stephen Hawking called AI "either the best, or the worst thing ever happened to humanity" (Herm, A., 2016). Indeed, this change will involve every part of the society at large, and of course, the way of doing business (Brock, J. K.-U., & von Wangenheim, F, 2019).

Today AI can be applied to many fields, from healthcare to supply chain. Among them, marketing is the area where is expected to obtain the most promising value impact, due to the high level of data that is possible to derive from the customers' interaction with the companies (Michael Chui, et al., 2017).

Marketing has always been influenced by technologies over the years, and currently is characterized by AI systems. Nowadays, these new technologies have led to the emergence and development of the voice assistants (VAs) market, which have the power to influence the future of digital marketing.

VAs are empowered by a combination of AI techniques, such as machine learning, deep learning, and natural language processing, and are defined as conversational agents that perform tasks with of for an individual. Even if they can perform a wide array of activities, today people use them mainly to carry out simple tasks, such as listening to music or asking for weather forecast (Mari, 2020).

However, in recent years, users have started to experience a novel functionality: they began to place order through VAs. Indeed, companies are developing their voice application to let customers purchase through smart speakers (Smith, 2020). The series of activities carried out to complete an order through a voice assistant goes under the label of "voice commerce".

Consumers with only a voice command can place orders through AI-powered voice assistants (VAs), without providing transactional information such as credit cards or address details. As such, VAs have the potential to significantly alter the process of product search and selection (Mari, 2020).

Considering this overall context, the present work aims at investigating the role of AI technologies and voice assistance in marketing by unravelling the potentials of these new technologies in influencing the consumers' buying behavior. Indeed, because of its peculiar characteristics, voice commerce has the potential to affect all the consumers' purchase journey stages, from the consideration to the post-purchase phase, and therefore, affect the way companies have to approach to this new channel.

Besides, it is analyzed the role played by consumers' trusting beliefs in this process. Indeed, although the rising of voice commerce, there is little literature about how this new channel will alter the consumers' shopping behavior. Furthermore, managers are left with little empirical advice regarding how to react to these changes and which consequences they will face if consumers start to copiously buy through this channel (Sun et al., 2019).

In order to investigate these research topics, the work is structured as follows.

The first chapter introduces the context of the dissertation, presenting an overview of AI, touching its history, the different definitions and classifications, and the main AI techniques. Then, it focuses on the role AI covers in marketing. Today, AI software helps companies to gather, analyze, and store consumer data. Moreover, Artificial intelligence marketing (AIM) is described as a method of leveraging customer data and AI systems to automate, optimize and boost marketing procedures to meet strategic objectives. Particular attention is given to the goal and the potential benefits of AIM. Finally, it is described which organizational framework supports better companies in this digital transformation, and what usually distinguishes leaders from laggards.

Then, the second chapter reviews the literature of voice assistant and voice commerce. Starting from describing VAs and the characteristics that have determined their success, the work gives short insights regarding who are the

developers of VAs, which are the AI techniques behind them, which is the profile of an ordinary VA user, and for what they are mainly used for.

Then, the voice commerce phenomenon is introduced. It is described the novel role played by VAs in this context. In particular, are explored background theories regarding how voice commerce works and all its possible consequences, looking from both companies and consumers perspective.

Finally, the last chapter examines the role of trust in VA during voice shopping. Specifically, an experimental study was conducted aiming at getting insights regarding the role of trust in the selection of a default private label option, and its implication for decision satisfaction. The topic was analyzed from the brand perspective, investigating how VAs' choice framing affect consumers' behavior and as a consequence brands owner.

A total of 60 students from the Università Politecnica Delle Marche were recruited online through an email informing about the study. In addition, because of the COVID-19 pandemic, the experiment was carried out remotely.

1. ARTIFICIAL INTELLIGENCE AND ITS APPLICATION IN MARKETING

1.1 ARTIFICIAL INTELLIGENCE: A HISTORICAL OVERVIEW

Despite the challenges in identifying the roots of artificial intelligence (AI), they can be reasonably tracked down to the first half of the 20th century. In these years, starting from the science fiction the idea of artificially intelligent robots began to spread worldwide. Then, generations of scientists, mathematicians, and philosophers stimulated and excited by this idea tried to make reality what they saw in the fiction (Haenlein & Kaplan, 2019).

Among them, the British mathematician Alan Turing studied the mathematical possibility of artificial intelligence. During the Second World War, he worked with a group of experts, with the purpose of decrypting a code used by the German army, called Enigma. The team was able to achieve this goal developing a code machine breaking, The Bombe, which today is considered the first working electro-mechanical computer. The potential of the machine in this task was far beyond those of the best mathematicians at that time. Realizing it, led Turing to question himself about the intelligence of such machines. In 1950, he published the article "Computing Machinery and Intelligence", in which he described how to build intelligent machines and he developed a criterion to prove whether a machine can

think (Rockwell Anyoha, 2018). He proposed the so-called "Imitation Game" intended to test them. Nowadays, this game remained famous as the "Touring Test"[1], and it is still used as a benchmark to assess the ability of a computer to mimic a human, so its intelligence (Haenlein & Kaplan, 2019).

Six years later, the term "artificial intelligence" was officially coined by John McCarthy, the mathematics professor at Dartmouth at that moment, on the occasion of the Dartmouth Summer Research Project on Artificially Intelligence (DSRPAI). The event, held in 1956, aimed at gathering the researchers from different areas in order to start a new research discipline around AI (McCarthy et al., 1955).

It was financed by the Rockefeller Foundation (Haenlein & Kaplan, 2019), and its proposal was written by John McCarthy, Marvin Minsky, Nathaniel Rochester, and Claude Shannon (Moor et al., 2006). All of them brought a great contribution to the field of AI and are considered the founding fathers of AI.

During the conference, it was introduced the Logic Theorist[2], a computer program able to emulate humans' ability of complex problem solving, developed by Herbert

[1] The test is conducted in the form of a game, in which three participants take part: a man A, a woman B, and a third person C. The latter is apart from the other two. His task is to distinguish who is the man and who is the woman, through a series of questions. The man A's purpose is to mislead C and drive him into the wrong identification, whereas B has to help C. The logic behind the test is that if the result (the percentage of correct answers) is the same whether the third subject is a human or a machine, then the machine can be considered intelligent (Turing, 1986).

[2] Its developers referred to the "Logic Theorist" naming it "the thinking machine". Its thinking underlies in the power of proving theorems in symbolic logic. In particular, it was able to solve 38 of the 52 theorems in Chapter 2 of Whitehead and Russell's Principia Mathematica (Gugerty, 2006).

Simon and RAND corporation scientists Cliff Shaw and Allen Newell (Rockwell Anyoha, 2018).

In 1957, in the wave of the Logic Theorist outstanding success, the three researchers, basing on the same fundamentals, created another program The General Problem Solver (GPS). Despite the name, the program was excellent in solving only a limited range of simple problems, like the Towers of Hanoi[3] (Haenlein & Kaplan, 2019). Both programs, the Logic Theorist and General Problem Solver, were developed using the programming language ILP (Information Processing Language), elaborated by the three scientists Newell, Cliff Shaw and Simon.

The Dartmouth Conference has given rise to a period of achievements in the area of AI, which lasted nearly 20 years.

A clear demonstration is ELIZA a computer program created by Joseph Weizenbaum, at MIT (Massachusetts Institute of Technology), between 1964 and 1966. ELIZA personified a therapist and was able to carry on a conversation with a human, thanks to its natural language processing tool. However, it had limits: it

[3] The towers of Hanoi: The Tower of Hanoi (also known as the Tower of Lucas named after its inventor) is a mathematical puzzle consisting of three rods and a many decreasing size disks.
At the beginning of the game, the disks have to be positioned in one of the three rods, putting them in decreasing order, forming a conical shape.
The goal of the game is to place the disks on a different rod respect to the initial one, following two simple rules: firstly, you can move only one disk at a time; secondly, you can place the disk only on another larger disk, not on a smaller one.
The puzzle can be solved with a minimal number of moves equal to $2^n - 1$, where "n" is the number of disks used.

worked by recognizing key words and then answered using what already told by the patient through open questions or pre-configured responses (Haenlein & Kaplan, 2019).

These two decades of successful innovations kept the enthusiasm very high guiding many experts to believe that in few years artificial general intelligence would be achieved. For example, in 1970, in an interview for the journal Life Magazine, Marvin Minsky shared his view that *"from three to eight years we will have a machine with the general intelligence of an average human being."*

Moreover, this promising period persuaded government agencies, such as the Defense Advanced Research Projects Agency (DARPA), to finance copiously many institutions to make advancement in the field of AI. However, this progress was arrested when the U.S. Congress started to complain about the large expenses on AI research. One of the problems was that the expectations were far too high than the reality, so this slowed down the initial enthusiasm. Even if the main principle was there, still the achievement of natural language processing, abstract thinking, and self-recognition was far away (Rockwell Anyoha, 2018). Consequently, firstly the British then the U.S. government stopped to sustain AI research, with the only exception of few universities.

Nevertheless, in the 1980s, DARPA return to finance the research, as a result of the massive Japanese financing. Notwithstanding, there were no further advancement for the next ten years (Haenlein & Kaplan, 2019).

The point of such arrest was that software like the General Problem Solver and ELIZA were Expert Systems, which means that they tried to mimic human decision-making process by formalizing its logic and reconstructing it in a top-down approach, as a series of "if-then" rules. Although Expert Systems were good at accomplish tasks suitable for such formalization, they were useless for tasks of different nature.

An iconic example of Expert System was Deep Blue, a chess-playing computer program, developed at IBM by the Chinese computer scientist Feng-Hsiung Hsu, and the Canadian Murray Campbell, in 1997. It was the outcome of years of hard working in trying to reach a supreme chess machine. Indeed, Deep Blue was able to beat the world champion, Gary Kasparov, after a six-game match. It was possible since chess is a logical game, based on general laws that can be formalized as required by the expert system. In addition, Deep Blue was able to elaborate up to 200 million moves per second and store thousands of already played games. However, such software would have not be able to recognize faces or to differentiate a dog from a human, when seen it in a picture (Haenlein & Kaplan, 2019). Essentially, they did not have the conditions necessary to defined artificial intelligence nowadays. Indeed, true AI are based on a bottom-up approach, which try to reproduce the human brain's structure, besides it collects a large amount of data to learn independently how to accomplish tasks. Like a child, they understand

how to identify a face, not applying formalized rules, but seeing hundreds of faces, making trials and errors.

Today, most of the AI applications are based on statistical methods. This approach has its origins in 1949 when the Canadian psychologist Donald Olding Hebb matured the so-called "Hebbian Learning"[4], a learning theory that initiated the studies in the research area of artificial neural networks and has inspired many scientists in this field (Haenlein & Kaplan, 2019). Artificial neural networks are computing systems, whose primary goal is to solve problems reproducing what a human brain does. Aforementioned systems "learn" to perform tasks by analyzing examples, generally without being programmed with task-specific rules. Nevertheless, these insights didn't deliver any immediate progress because the computer processing power at the time wasn't enough advanced to support such work on artificial neural networks.

In recent years, it is possible to find artificial neural networks in the software AlphaGo developed by Google's DeepMind. Firstly, in 2015 was realized AlphaGo, then in 2017 AlphaGo Zero which is an updated version[5], both were able to beat the current world champion at Go, a famous Chinese strategy game

[4] In the theory Hebbian, proposed a mechanism explaining how neurons moves in the process of learning. Today, usually people refers to the Hebbian Learning, meaning a mathematical abstraction of the principle proposed by the psychologist.

[5] The difference between them is that AlphaGo learned to play by challenging both experts and no-experts, whereas AlphaGo Zero gains the knowledge only competing again itself without the human help, but gathering many years of human experience in three days.

considered one the world's most challenging game. What enabled such systems to master the human ability was the progress made in the area of Deep Learning and Reinforcement Learning, which are specific types of artificial neural networks[6].

The purpose behind the creation of these programs is the willingness to invent general-purpose learning systems able to find a solution to the more important scientific problems (DeepMind).

Nowadays, Artificial Intelligence entered everyone daily life and it is applied to several areas, such as marketing, supply chain, banking, and health care. This was possible thanks to the progress made in computing power, the availability and the capabilities to store Big Data, and the improvements made in artificial neural networks.

[6] The "reinforcement learning" is a process inspired by how the animals learn, through experimentation and reactions. AlphaGo Zero can replicate this thanks to the powerful artificial neural network that for each turn of the game observes the current state and calculates the possible moves and their probability of being successful. This neural network updates and strengthens itself after each game.

1.2 AI: DEFINITIONS AND CLASSIFICATIONS

In its most basic definition, artificial intelligence (AI) is intelligence exhibited by machines. Usually it is regarded as robotic, but actually, it is an umbrella term that includes a broader range of technologies aiming at mimic human capabilities (Weber, 2016).

At the current stage of the research, it is hard to give a unique interpretation of what goes under the label of Artificial Intelligence. This research field is moving fast: machines regarded as surprisingly intelligent few years ago today are not anymore so remarkable, due to the conspicuous technological advancement. Besides, now we count many applications of AI, so depending on what one prioritizes, there could be different AI definitions.

Generally, over the years, the definition has been given in comparison to the human intelligence. For instance, when John McCarthy coined the term, in 1956, defined it as the purpose of "making a machine behave in ways that could be called intelligent if a human were so behaving." Likewise, Minsky referred to it as *"the science of making machines do things that would require intelligence if done by men"* (Stonier T., 1992).

In 1995, Norvig and Russell in "Artificial Intelligence: A Modern Approach" highlighted four approaches that historically have defined Artificial Intelligence. In particular: *thinking humanly*, *thinking rationally*, *acting humanly*, and *acting rationally*, as illustrated in the table below (Table 1.1). The first two are related to

the reasoning and thought process (thinking), whereas the latter two regard the behavior (acting). Moreover, the definitions in the left, judge the outcome in respect to its closeness to the human performance. Those in the right are assessed against an ideal metric, the rationality.

Thinking Humanly	**Thinking Rationally**
"The exciting new effort to make computers think… *machines with minds,* in the full and literal sense." (Haugeland, 1985) "[The automation of] activities that we associate with human thinking, activities such as decision-making, problem solving, learning…" (Bellman, 1978)	"The study of mental faculties through the use of computational models." (Charniak and McDermott, 1985) "The study of the computations that make it possible to perceive, reason, and act." (Winston, 1992)
Acting Humanly	**Acting Rationally**
"The art of creating machines that perform functions that require intelligence when performed by people". (Kurzweil, 1990) "The study of how to make computers do things at which, at the moment, people are better." (Rich and Knight, 1991)	"Computational Intelligence is the study of the design of intelligent agents." (Poole et al., 1998) "AI… is concerned with intelligent behaviors in artifacts." (Nilsson, 1998)

Table 1.1: "Some definitions of artificial intelligence, organized into four categories". (Russell & Norvig, 2010)

Thinking humanly means solving a problem through cognitive functions; *thinking rationally* indicate using the logic; *acting humanly*, is what can be verified by the Turing Test, so weather a machine behave in a way undistinguishable from human;

finally, *acting rationally* stands in obtaining the best possible result given the available knowledge (Russell & Norvig, 2010).

Lately, Michael Haenlein and Andreas Kaplan, summing up the publishing from famous world experts, defined AI: *"a system's ability to interpret external data correctly, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation"* (Kaplan & Haenlein, 2019, p. 17). With these words, they wanted to highlight how AI reach its objectives. This definition is the one that will be adopted, since it seems the most suitable to the purpose of this dissertation. Furthermore, this definition allows drawing the boundaries of artificial intelligence with respect to IoT and Big Data, as the three concepts are often confused.

IoT (Internet of Things) indicates the idea that things or objects can talk and interact with each other. The aim is to permit things to receive and send data through the Internet without human intervention. What enables them are sensors and software able to gather and transfer the data (Kaplan & Haenlein, 2019).

On the other hand, Big data can be described as a set of information, characterized by a large amount (Volume), collected from multiple sources and in multiple formats (Variety), generated quickly and frequently (Velocity), and being sure about their accuracy and quality (Veracity).

Big data are a wider concept than IoT since the data collected could derive also in different forms, such as from social networks or an internal company's database.

Both can be seen as a way to acquire external data to use as an input for AI. Indeed, AI uses this large amount of data to recognize the underlying rules and patterns. For example, machine learning, a subset of AI, requires a huge quantity of data to be trained and learn how to perform certain tasks, without being programmed to do so (Kaplan & Haenlein, 2019).

Consistently to the definition, there are different classification of AI depending on which aspect you want to consider.

For instance, taking into account their evolution in time, they can be classified into (Kaplan & Haenlein, 2019):

- **Artificial Narrow Intelligence (ANI)**, also known as weak AI: this type of software has capabilities below the human level, since it does not own its intelligence elasticity (Wirth, 2018). Indeed, it is tasks-specific, so it is designed to complete only a certain activity, in which can even surpass human intelligence, but it would become useless if applied in another area since it has to be re-trained from the scratch or changed. Today Artificial Narrow Intelligence can be found almost everywhere, thanks to the development of Machine Learning and Deep Learning processes. Examples are Google Search, image recognition systems, and personal assistants such as Siri, Alexa and Google Home.
- **Artificial General Intelligence (AGI)**, also defined strong AI, it describes a kind of system able to achieve the human standards and potential, because

it has the same intelligence elasticity (Wirth, 2018). AGI can perform independently many activities in different areas, reaching or beating the human intelligence. Like people, it is able to think and propose different scenarios to address problems. However, it does not exist yet.

- **Artificial Super Intelligence (ASI):** it defines a system a step ahead of the human level and it might be created in the future. It will be self-aware and own an intelligence able to outperform the most clever and talented human, in any field. It will not only understand the human logic and try to replicate it, but also apply intelligence to solve any kind of problems, from the math to the art, and it will own social skills and general wisdom. In this sense, it will make the humans superfluous, since it will have capabilities inherent to areas generally bound uniquely and strictly to the human domain.

Looking the concept from another perspective and focusing on the AI business use, AI can be classified according to the three type of competences: *cognitive intelligence* (competences related to path recognition and systematic thinking), *emotional intelligence* (adaptability, self-confidence, emotional self-awareness, achievement orientation), and *social intelligence* (empathy, teamwork, inspirational leadership). According to the management literature and specific studies, these are the skills that resulted to be present in those managers and employees who had a remarkable performance during their job (Kaplan & Haenlein, 2019).

It's easy to understand how the cognitive intelligence can be helpful to classify AI, because today most of the companies use this type of AI. On the other hand, it could be difficult to imagine AI systems that truly possess emotional or social intelligence. However, they can be trained to identify emotions and react as desired to them. Since individuals can learn how to perform these skills, the AI software can be able to imitate them.

- **Analytical AI:** shows the features of the cognitive intelligence. These types of software gain knowledge and learn through the experience, and use it to make future decisions. For example, the face and image recognition or fraud detection.
- **Human-inspired AI:** has characteristics consistent with the cognitive and emotional intelligence. During the decision making process these software are able to combine competences of both intelligences. Therefore, along with having a cognitive representation of the world and using the past data for the learning purpose, they are able to understand and analyze human emotions and consider them to solve problems. What enables these systems are the facial recognition or the voice analysis. Companies usually use them during the customer service, to understand whether the customer is frustrated or satisfied and react accordingly.
- **Humanized AI:** possesses elements of all the three competences (cognitive, emotional, and social intelligence). They have not been invented yet due to

the technology limitations, but probably this idea would become reality in the long-term future. What will distinguish it from the previous two types of AI, will be the fact to be self-conscious and self-aware in their interaction with others. They could find their application in many field, among them in the healthcare to provide support in the elderly care sector, for instance to those senior people who lives alone.

	Analytical AI	Human – Inspired AI	Humanized AI
Cognitive Intelligence	✓	✓	✓
Emotional Intelligence	✗	✓	✓
Social Intelligence	✗	✗	✓

Table 1.2: "Types of AI systems". Table elaborated by the author.

Finally, considering how of AI learn from the past data, it is possible to classify it in three wider categories according to the learning process implemented (Kaplan & Haenlein, 2019):

- **Supervised learning methods:** during the supervised learning it is used a full set of labeled data to train the algorithm. It means that a given set of inputs it's associated with a given set of labeled outputs, tagged with the right answer. For instance, starting from a large labeled dataset of fruit

images, the software will learn which picture shows strawberries, which are the peaches and which the apples. Therefore, when the software sees a new photo it can forecast the right label, comparing it to the picture in the training examples. Supervised learning includes methods such as linear regression or classification problems. Indeed, it is the most appreciated by the managers because it involves something they are already used to and can control the accuracy of the algorithm by evaluating whether the solution seems correct or not.

- **Unsupervised learning methods:** a training dataset is entered into the system without giving specific commands and not having an already known right outcome. In this case, only inputs are labeled, not the outputs. Therefore, the algorithm needs to discover the structure from the data, analyzing them, and obtain from them meaningful insights. Two examples are the cluster analysis, in which the algorithm purpose is to group members sharing similar characteristics, and speech recognition. The answer is derived from the algorithm itself, so it is not possible to assess the accuracy and correctness of the resulting output. This could make managers feel unease.
- **Reinforcement learning:** the systems have to find the optimal way to achieve a desired outcome, given a series of actions that it can take. When

it takes good decisions, it gains a bonus. The purpose is to predict the best move to obtain the maximum final reward.

1.3 HOW DOES AI WORKS?

AI operates by integrating large amounts of data with fast, repetitive processing and intelligent algorithms, enabling the software to learn automatically from models or data characteristics (SAS, Analytics Software and Solution). Although AI is known since the 1950s, only recently it has become of public interest primarily thanks to the improvements in computing power of the last decade, which made it cheaper and convenient to use AI.

At the same time, recently we have experienced an increase of the internet-connected devices and smart devices (IoT), which helped to gather and share structured and unstructured data. They can be seen as input data to empower and train AI systems (Kaplan & Haenlein, 2019). The availability of data, collected in this way or through other sources, played a critical role. Big data are a highly enabling element, considering that the more data is available and the more data sources are included, the higher will be the algorithm's ability to make accurate predictions. However, their management is precisely the most complex part of the process. Data on their own are not useful unless it is possible to understand how to extract value from them.

As already mentioned in the previous paragraph, AI is an umbrella term, which includes many different, but overlapping technologies.

For the scope of the dissertation, the author in the following paragraphs will focus only on machine learning, deep learning, and natural language processing (NLP) to which are directed the most investment activity worldwide (McKinsey & Company).

1.3.1 Machine learning

Nowadays AI is already giving an important contribution to many sectors. Indeed, it is possible to find it almost everywhere, and usually it comes in the form of machine learning, the most significant subset of AI.

The American Tom M. Mitchell, in one of the classic textbooks in the field, defined machine learning stating that *"a computer program is said to learn from experience E with respect to some class of tasks T and performance measure P, if its performance at tasks in T, as measured by P, improves with experience E."* (Tom M. Mitchell et al., 1997, p. 870–877).

Therefore, in simpler words, ML learns from the experience applying statistical techniques. This involves training algorithms to perform a specific task, by learning from previous data and examples, rather than being pre-programmed to do so (SAS,

Analytics Software and Solutions). Machine learning deals with structured and labeled data (IONOS, 2020).

In practice, for instance, it is possible to make the ML algorithm understand the sentiment of 1 million customer reviews, distinguishing which one is positive, neutral or negative. The learning phase involves taking a sample of these reviews and label them according to which sentiment they show among the three options. Then, feed the training data into the machine learning algorithm. With enough training data, it is able to recognize patterns and finally recognize the sentiment of the reviews completely on its own. To be sure of its quality, their abilities can be tested, by feeding the machine with raw data and assessing the quality of the outcome. On a regular basis, it is recommended to re-labeling manually the items in case of mistakes to teach the algorithm to learn from its errors and improve (Scholz, 2020). Therefore, it learns in a similar way of a child, namely from others and from its own mistakes. However, it is still behind the human level. Indeed, when the results are not those expected it has to be retrained through the human intervention.

As anticipated above, generally to be effective and understand how to perform a task, machine learning algorithms need a large amount of input data that are analyzed and then used to identify patterns and to predict future behaviors. The more they acquire and analyze data, the more they improve and give better predictions. Finally, they store the feedback generated by this process (John Allen,

2020).

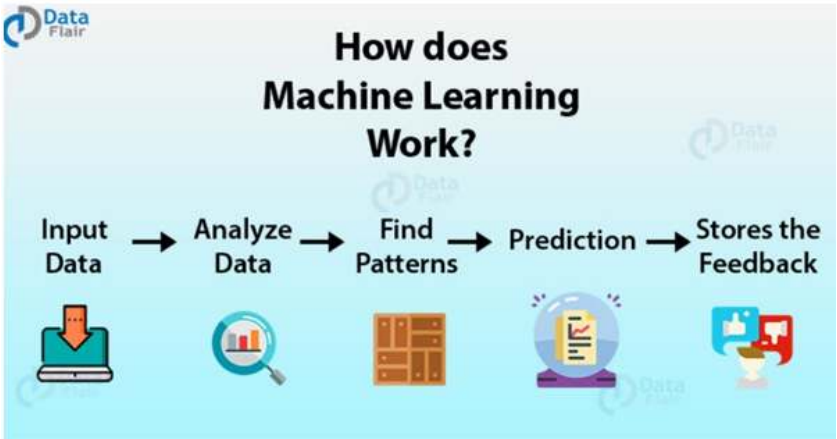

Figure 1.1: “How does Machine learning work?” (DataFlair, 2020)

Nowadays, machine learning is increasingly present in our daily lives, considering that every time a person is browsing on a search engine, like Google or Yahoo, he is using machine learning. Moreover, it applies to various fields from the anti-spam filter, to the streaming video or music services. Taking into consideration the latter: in this case, those algorithms can accumulate data from the users basing on what they search, and then use this knowledge to suggest them new songs or contents, according to their past behavior, and trying to predict what they could like. Finally, machine learning is exploited in marketing to deliver a better customer experience, for instance through the recommendations. Famous examples are “customers who

bought this item also bought this…" (Amazon), or "you might be interested also to this".

1.3.2 Deep learning

Among the machine learning techniques, deep learning is the most important one. The lines between AI, ML and deep learning are blurred, and the three terms are sometimes used interchangeably. To clarify the concept and understand how to distinguish them, venture capitalist Frank Chen, during an Ai presentation, specified that: *"Artificial intelligence is a set of algorithms and intelligence to try to mimic human intelligence. Machine learning is one of them, and deep learning is one of those machine learning techniques".*

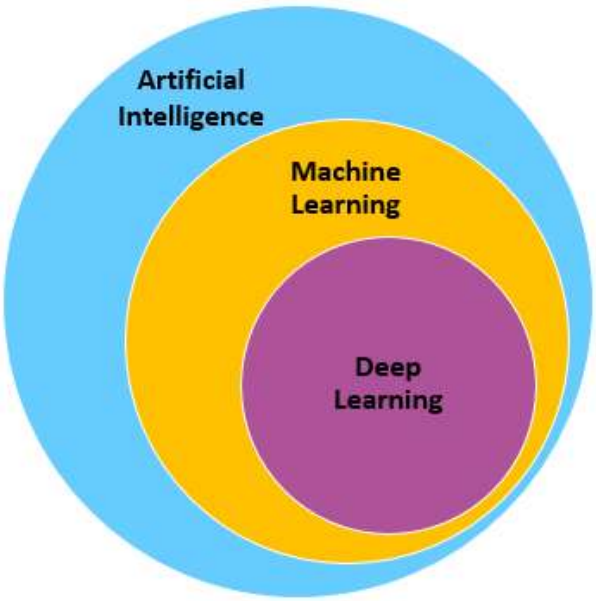

Figure 1.2: “Machine Learning and Deep learning: two AI subsets.” Figure elaborated by the author.

For many Deep learning is the next step in the evolution process of trying to shrink the gap between artificial and human intelligence.

Deep learning algorithms are known as artificial neural networks, and they involve a set of techniques that simulate the human brain learning processes. The system operates through many-layered neural networks (IONOS, 2020). They manage to replicate the human brain by exploiting a powerful computational capacity able to support different layers of calculation and analysis, and the improved learning techniques capable of identifying complex models in a large amount of data (SAS, Analytics Software and Solutions). Their structure allows deep learning networks to do far more than machine learning algorithms: they can solve hard problems without introducing pre-processing data. This type of system can make sense of unstructured and unlabeled data sets. At each level, the system decides how to categorize the data in question, following its specific procedure. Therefore, the approach is particularly suitable when not all aspects of items can be categorized in advance.

An essential requirement is that the training set must be very large. Deep Learning requires much more data than Machine Learning. In addition, this technology is more complex to implement. It requires more computer resources and is much more

expensive than Machine Learning, so it is not appropriate, at least for the moment, for many companies.

The most common applications include image, speech recognition, and fraud identification (IONOS, 2020).

1.3.3 Natural Language processing

Natural language processing (NLP) represents another branch of artificial intelligence, which has many applications today, and it deals with a computers' ability to understand, interpret and manipulate human language. The main aim is to reduce the gap between human communication and computer understanding. Human beings and computers do not share the same language. People may speak different languages according to the country of provenience, such as English, Italian or Chinese, on the other hand, computers communicate through programming languages, which are not made by words, but they are composed by symbols, letters and numbers combined to produce logical actions. Therefore, thanks to NLP, computers can communicate with individuals in their own language, and they can carry out tasks related with it. NLP is able to read text, hear speech, interpret it, measure sentiment and establish which parts are critical (SAS, Analytics, Software and Solutions). For example, in a company context, NLP can help to handle large volume of textual data making an accurate sense of them, in short time. Considering

the burden of data overload which organization have to handle every day, it would imply a great contribution, in terms of both time saving and superior performance, indeed it enables firms to do something that would not be possible relying only on human forces. Automation will be decisive, in this regard, given the huge amount of unstructured data generated daily by different users and sources. Besides, NPL keeps pace of text analytics, which counts, groups and categorizes words with the purpose of derive insights, trends or patterns. For example, nowadays the two technologies together are applied in social media analytics, where they allow tracking awareness and sentiment regarding certain themes and discover key influencers.

NLP it's a powerful technology, and what enables its functioning are several different techniques used for understanding how people communicate, which is particularly complex, since it includes the ability to interpret the intrinsic ambiguity of human language. For example, people talk using dialects, write with abbreviations, or misspell words. NLP achieved it with the help of statistical techniques, machine learning methods, and rules-based and algorithmic approaches. Generally, NPL divided language into shorter, elemental pieces, trying to understand relationships between the pieces and explore how the pieces work together to create meaning. NLP is able to carry out a syntactic and semantic understanding.

Going more in deep, NLP is the general concept, which includes the different software that deciphers or produces human language, both by speaking or writing. In specific, NLP is composed by two subsets: Natural Language Understanding (NLU) and Natural Language Generation (NLG).

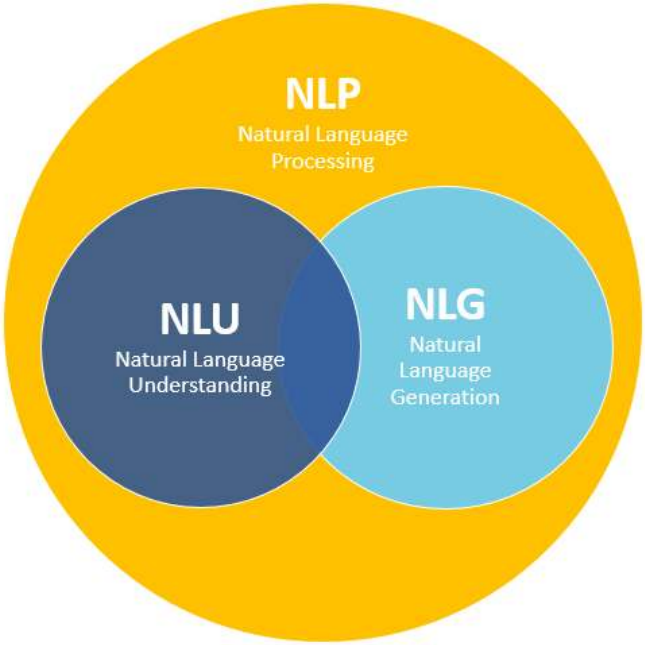

Figure 1.3: "Natural Language Generation and Natural Language Understanding: two subset of Natural Language Processing." Figure elaborated by the author.

NLU is responsible for understanding the intent, considering the grammar, the context and the word ambiguity. On the other hand, NLG as defined in the book "Artificial Intelligence: Natural Language Processing Fundamentals", is the *"process of producing meaningful phrases and sentences in the form of natural*

language" (Sciforce, 2019). In practice, NLG is what happens when a computer *write* language, its processes turn data into text, so it to generates written or spoken narrative starting from a dataset (Narrative Science, 2017).

To have a concrete example, with the available technology today it is possible to interact with devices, such as Alexa, a personal assistant supplied by Amazon, to which you can say "Alexa, let's play some music", and the device will start playing music. Considering this interaction, the device activates itself when it hears its name (e.g. Alexa), then is capable of understanding the meaning of your spoken request, figuring out which is your intent, then execute the command in few seconds. This complete interaction is possible thanks to the whole NLP technique, together with other AI elements, like machine learning and deep learning (SAS, Analytics, Software and Solutions).

1.4 ARTIFICIAL INTELLIGENCE MARKETING (AIM)

Marketing, over the years, has been influenced by technology.

Starting from the Internet in the 1990s, we have an increasing use of CRM[7] (Customer Relationship Management) software in marketing, aimed at having a direct contact with the customer. This goal was achieved by collecting compiled

[7] CRM is a technology that supports the company in the process of storing, and analyzing customers' data. The aim is to effectively and efficiently manage the entire relationship with customers and potential customers, making them loyal. Besides the system helps the company to stay connected to customers, streamline processes, and improve profitability (Salesforce, 2019).

lists filled with the customer's information in databases. The sources of these data usually were application forms for free products, product warranty cards, or subscription forms. Then, the companies could send emails to the list of customers or potential customers anytime they wanted to promote products or services (Database Marketing). In these years, organizations used a single channel, one touchpoint to get to the customer.

Then, in the 2000s, the advent of new platforms, such as social media and the mobile, led to a multi-channel interaction with the customer. Still, companies handled the different touchpoints independently. The keyword was the engagement, organizations wanted to motivate people to connect with them and to create communities (Online marketing).

In 2010s, another advancement in technology leads to further change: it started the era of Big Data and cloud (Data-driven marketing). It shows the way to hyper-personalization, seamless, and cross-channel experiences, which allow contextualizing messages. The focus was to deliver the right message, to the right moment, through the right means.

Nowadays, in the 2020s, it is starting a stage defined by cognitive systems (AI marketing). Cognitive systems that enable to increase the relevance of content and predicting the next steps to deliver a superior experience to the consumer. This should lead to omni-channel. What marketers want to do is not only personalize, but also make the relationships at scale. AI allows them to capture crucial

information about an individual and make it available to those departments in contact with the customer, typically marketing and customer service (Mari A., 2020).

Evolution Area	Database Marketing	Online Marketing	Data-Driven Marketing	AI Marketing
Decade	**1990s**	**2000s**	**2010s**	**2020s**
Technology	Internet	Social Media & Mobile	Big Data & Cloud	Cognitive System
Achievement	Direct-to-consumer	Direct-to-community	Hyper-Personalization	Relationship at scale
Channel	Single Channel	Multi-Channel	Cross-Channel	Omni-Channel
Goal	Contact	Engagement	Conversion	Relevance
Interaction	Personal	Individual	Contextual	Predictive
Software	CRM	Social CRM	Content Automation	AI-Powered Platform

Table 1.3: “From database marketing to AI marketing”. (Mari, 2020)

Today we are entering a new era: the age of the customer. This definition goes to underline the shift of the power from companies to customers. Essentially, the age of the customer has changed and continues to change the rules of business (Paper & Sizmek, 2017). The customer empowered by the technology has more information, authority, and higher expectations than ever before. If a company is not able to satisfy him, he will find what he needs elsewhere (Salesforce Report, 2017). For that reason, firms are challenged to enhance themselves and elevate their offering, being flexible and ready to align it accordingly to the customer willingness (Avasthy, 2017).

The higher consumer expectations, together with the explosion of digital and data touchpoints, are leading to an increasing market complexity that companies are facing today. For that reason, they are starting to recognize the value of AI marketing software (Mari, 2019). Indeed, these systems allow companies to elaborate a huge amount of data in real time, something that humans alone would not be able to achieve, since it exceed their cognitive capacities. Information is becoming a key asset and analytical skill that is fundamental for the whole business well-functioning (Gartner, 2019). Thanks to the more accessible information, companies can deliver better customer experiences, automating some tasks and saving time to be creative and to focus on strategy. Artificial Intelligence Marketing (AIM) represents a form of doing marketing that exploits artificial intelligence systems to automate, optimize and boost marketing procedures to meet strategic objectives (Mari, 2019).

In a 2017 discussion paper, Mckinsey & Company estimated that AI techniques have the potential to create between $3.5 trillion and $5.8 trillion in value annually across nine business functions in 19 industries. The value changes depending on the applicability to the particular case, as well as the availability of enough data, and other required elements. Among them, marketing together with sales and supply chain management have the most promising value impact. For example, industries such as retail and high tech will be those with the higher potential from marketing and sales because of the high level of data that can be derived from the customers'

interaction with the companies. Among them, e-commerce platforms will have even more advantages given their particular nature, which implies for sure a digital customers' information availability, such as click data or the time spent on a web page. According to the data collected, companies can personalized promotions, prices, and products for each customer dynamically and in real time. Thanks to these new opportunities, AI will generate up to $2.6T additional value in Marketing and Sales (Michael Chui, et al., 2017).

Companies worldwide, recognizing its potential, are increasingly investing in AI technologies, precisely in 2016, the investments were between $26 billion and $39 billion. Most of them include internal R&D spending by large, cash-rich digital-native companies like Amazon, Baidu, and Google. However, as stated by Mckinsey & Company, among 3000 AI-aware companies studied in their research, only 20% of them were using AI in a core part of their business process or at scale. For the rest, the adoption is still in an experimental stage (Jacques Bughin, et al., 2017).

Generally, organizations are investing in AI marketing mainly to drive revenue growth, better serve existing customers, meet rising customer expectations, remain competitive, or strengthen their brand (Avasthy, 2017).

1.5 AIM: GOAL AND BENEFITS

AI will transform and influence, not only our personal life but also how firms make decisions and interact with their external stakeholders. The question is not anymore, whether AI will play a role in these elements, but which role it will play and how humans and AI will live together. Which decision should be taken by AI? Which by humans? Which in collaboration? These are the main issues companies will have to address (Haenlein, M., & Kaplan, A., 2019).

Going in deep, AI, and in specific machine learning, in the company context have three different goals: replace humans (automation), reduce workload for humans (optimization), or enhance humans' skills (augmentation). A strategy to be successful needs to include the three elements together. Accordingly, the managers should understand and assess how and when to combine employees and machines to deliver a superior brand experience, enhancing each other's strengths. Moreover, in each step along the customer journey, they have to find an equilibrium between the two forces. Focusing on the three goals of AI for marketing, let's see their explanation (Mari, A., 2019):

- **Automation:** historically has been thought to automation as a way to boost the performance through intelligent algorithms, reducing some inefficiencies, and at the same time cutting costs of human labor. Nowadays, its primary purpose is not anymore only automating internal processing or reducing costs. Marketing automation enabled the automation of the

customer experience. Therefore, it is possible to achieve results, not obtainable merely by humans. Companies can implement solutions that delight customers with proactive and automated services.

For example, Netflix uses predictive algorithms to make automated recommendations, which entail the 80% of the movies watched on the platform.

- **Optimization:** it means using AI algorithms to reduce the human workload. Precisely, companies are using it to optimize processes, decrease expenses and time wasting, and deliver a better outcome. This can be done without a substantial increase in manual work. It also implies an increase in productivity, thanks to the time saved, for example not segmenting customers. Marketers can infuse AI into the brand building process, optimizing customer acquisition and retention, since it allows marketers to engage with consumers across channels and provide optimized customer journeys.

  Olay's Skin Advisor represents an example of customer education through AI-optimization. Skin Advisor is a deep learning powered app able to find out the people "skin age" and recommend specific products accordingly. Olay, after having introduced the skin advisor, announced the outstanding benefit obtained, indeed the company had twice the conversion rate than

before, engaging with 4 million consumers in the meantime.

Some marketers see the optimization as a way to concentrate and put the effort on strategic interactions with customers, and provide immediate intervention. For example, giving up sending thousands of emails prioritizing real-time customer-agent communications, such as chat bots. Optimization will help to have a more consistent approach to targeting, according to German Ramirez, Founding Partner of The Relevance House, who said, *"I have seen a fair amount of cat food advertising in my life and I do not own a cat or plan to own one. Every single penny invested in having me watching an ad for anything related to cat food was wasted."*

- **Augmentation:** AI algorithms can play the role of enhancing humans' skills, adding layers of intelligence. When the goal is the augmentation, firstly, it is critical to understand in which tasks the human or the machine have the primate, so that you have in mind what has to be necessarily done by people and what is better done by machine. Then, managers have to figure out how to combine and intersect the work of the two forces to achieve superior results.

  Of course, at least for the moment and for the near future, human beings have supremacy in critical thinking and in using common sense. They have the capacity to abstract reality considering the big picture of the problem.

They can think in uncertainty context, exploring the situation from different sides, and suggesting hypotheses. On the opposite side, algorithms are better off in processing data quickly, with a high level of accuracy, and in bringing solutions rapidly, enabling a company to be reactive.

Currently, there are many organizations, which are experiencing the augmentation, and in most of the time, machines boost the human ability to draw conclusions. Speaking about numbers, Capgemini stated that 86% of those managers implementing AI solutions at scale firmly believe that machines can greatly augment human output.

Regarding the augmentation application, an example is given by the implementation of the so-called Speech Analytics in most advanced call centers. Nowadays, many call center can take advantage of software able to make instantaneous sentiment analysis, analyzing the audio data, and detecting certain emotions expressed from the customers during the interaction with the employee. For example, the software can capture things like the customer tone of voice, whether he is satisfied or frustrated, or is getting upset. Then, having a real-time response by the machine, the employee readjusts his action considering those insights. So, basing on customer's needs, wants and expectations, he can figure out how to best address any issues. This enables the company to deliver a better customer experience.

In most of the cases, when companies decided to invest in AI marketing to fulfill one of the goals aforementioned, they realize that AI helped the organization to achieve three specific benefits (Mari, 2019):

- (Hyper) Personalization of customer experience across channels or touchpoints, and personalized engagement;
- Predicting customer behavior;
- Closing the insight-action-gap.

Personalization takes place when companies determine, generally basing on previously gathered customer data, which marketing mix is appropriate for the individual. Personalization is a process that connects customers and marketers and reinforces their relationship. The way the company builds customer relationships is a critical factor that influences customer engagement (CE). Respectively, customer engagement is defined as a psychological state that occurs when the customer is cognitively, emotionally, and behaviorally connected with the brand. The three levels of connection have to be respected at the same time.

AI can help companies to achieve a great degree of personalization and this is believed the major factor behind its popularity. Furthermore, it is perceived as unobtrusive: most of the time users do not even recognize it when they faced it.

Companies should exploit its potential and implement these new technologies to provide a greater personalization, and then improve CE. In order to achieve it, all the data related to the customer interactions with the brand are required. Therefore, managers should realize a digital curation strategy, which is defined as *"the management and preservation of digital material to ensure accessibility over the long-term"* (D. Abbott, 2008), in order to keep information organized and ready to be utilized in the moment of need. It has been demonstrated that CE improved with curation. Specifically, curation in personalized engagement marketing *"is the automatic machine-driven selection (of solution) of products, prices, website content, and advertising messages that fit with an individual customer's preferences"* (Kumar et al., 2019, p. 138). Customers' infinite options and information are curated in a personalized way by AI tools, going beyond what humans are capable of. Marketers can leverage computer speed and power to considerably scale up in real-time without losing accuracy in results. Moreover, Sasha Srdanovic, from Microsoft, said *"Machine learning helps to move away from former customer segmentation and drive real-time automated segmentation. We understand what the customer is looking for right now and what he might be interested in next."* (Mari, 2019). Nowadays, one of the companies' key priorities is creating a hyper-personalized omni-channel customer experience. Therefore, tailoring the communication and the offers based on what the individual demonstrated to prefer (through the collected data), keeping attention in making

always perceive the same brand value across all the touchpoints. Companies should become customer-obsessed. (Avasthy, 2017). The shift from simple segmentation to dynamic segmentation can be seen with the lens of achieving a higher personalization. This is a common tactic among higher performers marketing teams (92%), composed by those extremely satisfied with the current outcomes realized as a direct result of their marketing investment, which are saying they are using or planning to use within 12 months dynamic content (The AI Revolution, Insights into the next Era of Customer Relationships, 2017). For example, L'Oréal Paris produced twelve different versions of a YouTube video to make it closer to the preferences of different customer segments. The company could arrange it thanks to insights provided by Google's AI-powered platforms, and generated from its fan base. The campaign lead to an increase of 109% in brand interest and 30% in purchase intent (Mari, 2019).

At the same time, Netflix can be considered to show an example of hyper-personalization. Netflix creates many different versions of banner, making them visible according to the people interests. The company understands basing on past data, what users like most and is able to deliver a personalized item, starting from the idea that a different visual attracts different people. For instance, if the person is a comedy lover, so mainly use Netflix to watch comedies, in the banner of the movie "Good Will Hunting" will appear an image of Robin Williams. From another user, the same movie will be promoted with a different banner, according to his

tastes. Therefore, the algorithms display content based on each member preferred genres and themes or based on the cast members preferences, for example.

Predict customer behavior implies using AI software to effectively handle data and extract value from them, enabling companies to make accurate marketing decisions predicting what customers want, so which action is more likely to succeed. These AI tools are also able to learn from the past customer interaction and keep improving as they are used, thereby elevating their value. Among them, the most common example is presented by recommendation engines, which match offerings to customers, basing on what they liked or bought in the past and guessing what they could find interesting in the future. This method is effective because it helps the customer to reduce "information fatigue" decreasing its cognitive load, and taking the responsibility of finding the best options. Indeed, today's abundance of information can lead the customer to be frustrated along the decision-making process (Kumar et al., 2019).

Predictive marketing has the potential to give a great contribution to companies, since it helps *"to recognize the customer as individuals, understand their needs, leverage their historical data, and predict their intentions, to deliver content and suggestions tailored to each customer, doing all in real-time"* (Paper & Sizmek, 2017). For instance, Otto, a German e-commerce implemented AI models to predict those products that will be sold in the next 30 days, with 90% accuracy.

They have a great amount of data, so they can look at previous seasons, trends among consumers, and what they are buying at the moment. Indeed, they use both real time and historical data. This enabled them also to have a significant advantage in managing the logistics: the system enables the company to automatically buy more than 2 million items per year from third party brands, and at the same time maintaining fast deliveries to customers (Mari, 2019).

Close the insight-action gap is a critical topic today among marketers because usually companies own an enormous amount of data but they do not utilize it. They have more than what they can process, so this leads to an inability to turn data into insight and then into action in short times. This often happens because most of the organizations handle the insight generation and marketing execution as separate activities. Moreover, the process of bringing insight into execution is still manual (Avasthy, 2017). Therefore, generating an accurate real time decision-making according to what emerges by data, represents a challenge for many companies that admit that their customer insight teams take too long to deliver insights, or are not able to use all their data when making customer decisions (Paper & Sizmek, 2017). This is the reason why many organizations are implementing AI software to address this problem. Seventy-two percent of companies surveyed by Avasthy (Forrester) said they were planning to invest in AI to drive real time interactions across channels or touchpoints.

Indeed, companies need to be relevant and provide solutions in the moment of customers' need or they risk losing opportunities. Soon, it won't be likely to see successful companies that do not make a strategic use of data. An intelligent use of data is essential to predict customer' preferences and to deliver timely, personalized customer experience. Therefore, the process of obtaining insight from data and perform marketing actions accordingly need to occur simultaneously (Paper & Sizmek, 2017). This will allow companies to build a direct-consumer relationship without being dependent on other centralized platforms (Mari, 2019). Finally, it represents the first step to switch from a 1-to-many marketing strategy to a strategy that is 1 to 1 and, eventually, 1-to-moment. This means reaching the customer in an exact moment of the customer journey, and delivering the most appropriate message depending on which phase he stands (Paper & Sizmek, 2017).

1.6 HOW TO SUCCESFULLY IMPLEMENT AI: DRIVING FORCES AND BARRIERS

AI is considered by many a technology that will lead to a radical transformation. This change will involve every part of the society at large, and of course, the way of doing business. Most of the managers are thinking about implementing AI and integrating it in all strategic facets of the firm's operations. However, at this stage, it still hard to understand how to act, since managers have little empirical advice on how to structure this process. Evidences highlight that, today, AI is generally

implemented, along with other technologies, in an overall context of digital transformation projects (Brock, J. K.-U., & von Wangenheim, F, 2019). It is wide knowledge that the technology alone does not represent a source of sustainable competitive advantage, so managers should look at AI with this awareness, since it is not so different from the other technologies. AI has to be incorporated into a specific general framework. A certain company environment and organizational characteristics are necessary to make it helpful in delivering superior performance (Mari, A., 2018). Companies should be sure they are prepared before implementing AI in their operations. The initial steps are largely strategic and have longer-term than short-term implications. Some elements can help organizations to understand whether they are ready or not for AI (Kumar et al., 2019). A research made by Brock and von Wangenheim (2019) reported that what distinguishes digital transformation leaders from the laggards can be identified in seven organizational traits. These are integrated data management, CEO priority, security strategy, digital processes, digital strategy, agility, and open innovation ecosystem.

Integrated data management is the most critical aspect, able to make a great difference, and it is strictly related to the fact that AI is dependent on data. Therefore, organizations able to handle customer and organizational data, without causing a data overload or gathering them in different formats, have an edge on others. For example, merging data from different sources (touchpoints, or marketing and advertising platforms) is crucial to create a single view of the

customer, which in turn is an essential condition to drive personalized and contextually relevant information (Paper & Sizmek, 2017). *CEO priority* relates to whether the manager prioritizes and leads the company transformation process, giving his support during the AI implementation.

Moreover, having defined and planned the execution of a data *security strategy* it is of primary importance, giving how much companies relying on online data. For example, it is essential to think about the management of access rights, intrusion detection, and disaster recovery mechanisms.

Digital processes concern the digitalization of the main business processes, as it is understandable by the name. In addition, there are high probabilities to fail if you proceed without planning your actions, on the contrary, you should develop and execute a *digital strategy* to digital transformation.

Organizational *agility* refers to a firm's ability to adapt rapidly and flexibly to market change, for example to new customers' needs or demand fluctuations. This type of organization have also a mindset characterized by a continuous willingness to reinvent themselves and they are able to do it quickly and with flexibility, as they learn and adapt during the process. Finally, the *innovation ecosystem* is defined as the creation of an open ecosystem for innovation, outside the company borders. Examples are looking for suppliers, customers, alliances, or partners.

In the same research, the two authors defined a framework for successfully implementing AI projects, in the context of digital transformation. With the acronym “DIGITAL” they identified seven areas in which a proper managerial action can imply positive results. “D” stands for data, “I” for intelligence, “G” for grounded, “I” for integral, “T” for teaming, “A” for agile, and “L” for leadership. Below is provided a short explication regarding the acronym meaning.

As previously mentioned above, *Data* are essential for AI functioning, therefore the manager should start with a data inventory check before initiating an AI project. However, data alone are not enough, organization need also to be *intelligent*. Indeed, companies should focus on developing human intelligence. For a successful extraction of value from AI, technical skills, such as expertise in new digital technologies, cybersecurity, and data science, are not the only requirement. Firstly, managers are demanded to own strategic capabilities, precisely in the form of awareness and understanding. Namely, awareness of what is required to start an AI project and what they can accomplish with its implementation, and the understanding of how to leverage this technology in the specific company context. Therefore, it involves an internal and external analysis of the company, looking at the company's strengths, its customers, and the industry in which the firm operates. Secondly, the researchers suggest a dual sourcing strategy: foster the existing internal skills, and at the same time acquire external talent. In this way, the company builds the necessary technical skill base to guarantee the efficient and effective

application of AI technologies. Finally, AI implementation requires time, as during this process project participants learn from the feedback provided by the system. Therefore, it is important to provide them with abundant time and funding, allowing for a "failure culture". Learning from the failures help to get more out of the AI projects.

Be *grounded* means that a firm should "start in small", and applying the new digital technology to improve their existing core businesses, rather than seeing it as a disruptive from the first steps. Therefore, the authors advise the companies to proceed with caution, and embark on more complex projects, only when enough experience has been accumulated. *"Start small, test, learn, and then apply more widely".*

Be *integral* refers to implement AI projects in support of the overall company-wide digital transformation efforts, so considering the big picture. It implies having a comprehensive approach, which takes into account six different elements: strategy, processes, data management, technology alignment, employee engagement, and culture. The presence of a digital strategy is what differs leaders from the laggards.

Be *teaming* is a concept strictly related to the creation of an "innovation ecosystem", presented above among the organizational characteristics. Indeed, companies are advised to establish a partnership with one or several technologies suppliers, from technology generalists (IBM or Fujitsu), to consultancies companies (Deloitte or PwC). This could provide two distinct benefits, firstly having access to

technologies, and secondly, taking advantage of the experience already accumulated by these partners. Given the today market complexity, few organizations will succeed without any assistance, since a series of capabilities, components and expertise will be increasingly necessary. For that reason, find the proper partner will be crucial (Paper & Sizmek, 2017). However, be teaming is not something bound only to this aspect, but it includes also suppliers, customers, and alliances partners from different industries. Developing an innovation ecosystem permits to source talent outside the firm. This is rewarding, especially because of the AI technical skill scarcity. Companies can choose between joining an already existing ecosystem and building a new one.

Be *agile*, as already partly explained above, signifies keeping the management of the AI project flexible during its entire duration, adapting the strategy according to the feedback given by the system or what was learnt.

Lead means that the manager needs to prioritize the firm's digitalization process, considering AI and other technologies. If AI is a fundamental enabler for AI technologies, leadership is what gives the right energy to achieve successful implementations.

This overall framework describes what is needed to successfully implement AI.

Nowadays, there aren't too many companies immediately ready to adopt these technologies and sharing the characteristics mentioned above, most of them are hesitant and held back by the high perceived challenges of implementing AI.

According to a Capgemini survey made in 2017, 64% of the respondent senior executives worldwide were reluctant to adopt this technology, because of a "lack of appropriate skills and talent within the organization". In addition, other barriers are presented by the technology, which is perceived as too immature, too complex, or too unproved to deploy at scale. Indeed, as claimed by another survey made by WBR Digital and Persado (2017), 76% of the respondents had a "confusion or lack of clarity for what AI can be used for", the 59% "distrust of introducing AI technology, and for the 52% the problem was the "lack of defined business case".

Another concern comes from the belief that employees cannot coexist with AI in the working contest. Consequently, employees are worried about being fired and substituted by machines. IBM coined and uses the term Augmented Intelligence to highlight the possibility of a collaboration with employees, rather a substitution, and at the same time to calm down the fear of job losses. Its goal is looking for an interaction, where AI can help people in their decisions making process, improve their performance, and their ability of problem solver (Mari A., 2019).

A survey carried out in 2016 from Weber S. found that 60% of internet users worldwide were very concerned about job losses, with an additional 29% somewhat concerned. This anxiety has been ongoing since the concept of AI started to circulate and represent one of the reasons why a large number of marketers are reluctant to adopt AI (eMarketer, 2016). Remarkably, this fear is shared also by millennials (those born between 1981 and 1996). Eight out of ten millennials

believe AI has the potential to at least partially replace their job, despite they are one of the generations most familiar with AI. For them, the anxiety is even higher than the other generation, since they are those who are entering the market today or at least those who have left more years to work (Weber, 2016).

Eventually, managers should open a dialogue with employees to address their fears. For example, showing them that recent studies (2017), estimated that 83% of AI implementers believe that the technology had created new job roles within organizations (Capgemini research).

Generally, it is not frequent seeing AI systems completely replacing human jobs and processes. It is more probable to observe an automation of certain jobs, but at the same time a creation of new positions. This happens because AI is a technology that needs human intervention for its development, installation, and training. So, there will always need of human support to supplement AI technology, regardless of how much sophisticated algorithms become. Despite AI algorithms are usually automated once in operation, AI is still highly technical, research-intensive, and human-centric activity. The job will change from executing repetitive tasks to teaching AI to perform those tasks for you. Allowing saving time for creativity and strategy. In this respect, Team One's Green stated *"Most people see AI as replacing the jobs within agencies, but I think it's just going to make people work more effectively. [We'll have] the ability to get rid of some of the repetitive tasks that we do."* Besides, Isobar's Meeker believes AI may result in some job losses but will

ultimately streamline marketing. He said there might potentially be less staff in the future, but that staff would be *"empowered by wicked information and systems that can do things that today feel magical—the ability to make decisions, get insights and deliver content at a level of accuracy that just far surpasses what we have today."* (Artificial Intelligence for Marketers 2018 : Finding Value, 2018).

Deciding not to adopt AI means facing the probability of being left behind. Companies that will not implement AI in the near future will hardly compete with the others. Nowadays, this reality is enhanced by the entry of millennials in the consumers market, which are overtaking the Baby Boomers purchasing power. Marketers should give the right attention to this phenomenon. Millennials are the generation most familiar with, and which has higher confidence in AI, respect Gen Xers (1965-1980), and Boomers (1946-1964). Their knowledge comes from direct experience with AI devices, whereas their major trust probably arises by the fact they grew with digital technologies, so it is something they are accustomed to (Weber, S., 2016). For example, as reported by a survey made by Weber S., millennials are significantly more likely than older generations to trust AI to babysit their children (45%). It is evident that millennials parents are a customer segment that deserves particular attention. Moreover, it is also a generation that expects more from companies, and this will emphasize even more in the future with Gen Z (1996-2010). Therefore, it would be better not to be caught unprepared.

2. VOICE COMMERCE: A LITERATURE REVIEW

2.1 THE VOICE ASSISTANTS: AN OVERVIEW

In the artificial intelligence panorama, it is necessary to consider a new trend that is recently rising: consumers are increasingly buying and using smart speakers. Therefore, Artificial intelligence, embedded in these devices, is becoming ubiquitous in people daily life, and thanks to smart speakers, AI is entering billions of consumers houses.

In the context of IoT (Internet of Things), smart speakers could play a central role in what concerns the smart homes' evolution, making the relationship with technologies more personal than ever (Mari A., 2019). They are known with many other terms, such as voice assistant, AI assistant, intelligent agents, virtual personal assistants, voice-enabled digital assistant, automated assistants, or virtual agents (eMarketer, 2017). They are becoming popular only in the last few years, thanks to the rapid progresses made in the field of AI, however virtual assistants have a long history, and the first attempts date back to the 1990s. Among them, remarkable

examples are presented by Intelligent Room[8] project at MIT and the ComHOME[9] project from the Interactive Institute. Especially the first one shared some characteristics with the current voice assistant, for example, to give a command, it was necessary to use the wake word "computer" at the beginning of the order. Notwithstanding, the technology at the time was too rudimentary to lead to significant findings (Bentley et al., 2018).

Nowadays, voice assistants are defined as agents supposed to interact with an individual in human-natural language. What identifies these devices is their ability to answer questions or follow a conversation as they would be living people (European Commission, 2018), and their capacity to accomplish several tasks with or for the end-user (Mari A., 2019). Indeed, they leverage a combination of AI techniques to emulate human conversations, for example, they can reply to people obtaining the information from different online sources, without having a specific set of commands or using a computer language (eMarketer, 2017). Moreover, they have the capacity of self-improving as they operate, and to better understand the interlocutor and the context (Mari A., 2019). In particular, the software embedded

[8] It was a system completely carried out in the laboratory, and never studied in a real home environment. To function it needed hundreds of meters of cabling. The project represented an intelligent environment controlled through voice and gesture commands, which could be used to control lights, play music, move blinds, or ask some general-purpose questions such as weather. The purpose was to study a way to pull the computer out into the real world of people, rather than pull people into the virtual world of the computer.

[9] A laboratory project to study the future dwellings, for example making smart homes. The commands were mainly given to initiate video calls between apartments.

in smart objects is enabled by AI technologies, in the form of machine learning (ML), deep learning (DL), and natural language processing (NLP), together with automatic speech recognition (ASR).

A voice assistant to process natural language have to follow four main steps. The first is speech-to-text and text-to-speech (also known as speech recognition), which implies converting speech to actionable data that means to transform the spoken words into a text form. It is a crucial phase, because an error made here can result in a completely wrong answer later. Therefore, it will make the following steps worthless.

Secondly, it is necessary a syntax and semantic processing, which is made of a syntax analysis, to understand the grammar, a semantic analysis, to understand the meaning of the words, and finally a pragmatic analysis to reach the meaning of the sentence, taking into account the context.

Then, it is the turn of the question-answering step, which consists of accurately obtaining and formulating the answer. So, the process implies finding information on the Internet or other sources, and originating a precise sentence.

Finally, it is the moment of text-to-speech (TTS), also known as speech synthesis, which is the last step and consist of artificially reproducing the human voice. Indeed, the text/answer has already been constructed, so it is only necessary to give voice to it. In this regard, smart speakers have a margin of improvement, since nowadays they sound too much robotic, and researchers have demonstrated that

consumers preferred and would trust more human-sounding speech (European Commission, 2018).

Today, thanks to the level of the technology achieved and the fast progresses made, these devices are becoming widespread, especially in the U.S. market, where there are more than 70 million owners. There the adoption rate skyrocketed since their introduction, and it is forecasted that it will overtake those of smartphones and televisions, as shown in Figure 2.1. (Mari, 2019).

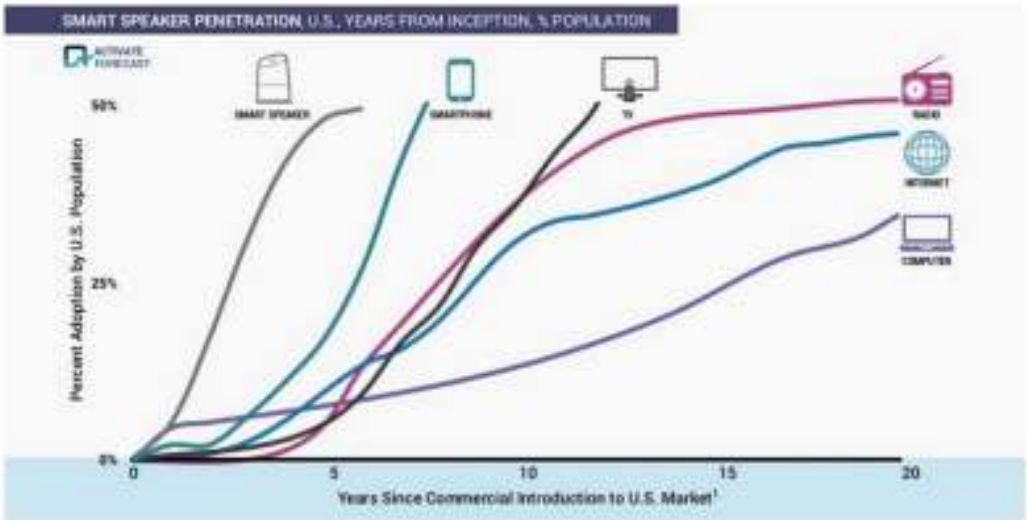

Figure 2.1: *"Smart speaker penetration, U.S., years from inception, % of the population".* Activate Tech & Media Outlook (2017).

Even if VAs are at an early stage of their product cycle, and many are still getting used to have around a device that listens and is ready to answer to their requests all day long, VAs are aggressively entering the market worldwide thanks to their low price. According to eMarketer research (2019), China will have the highest number

of smart speaker users, with 85.5 million smart speaker users in 2019, overtaking the US (74.2 million users). However, penetration, which is calculated in the percentage of internet users, will be higher in the US (26.0%) than in China (10.0%). The US had an advantage since Amazon Echo was launched in 2014, whereas JD.com's DingDong arrived in China in 2016. On the other hand, for what concerns the European adoption, smart speakers are most widely used in the UK, at 22.4% of internet users, followed by Germany (17.2%) and France (14.0%) (Corey McNair, 2019).

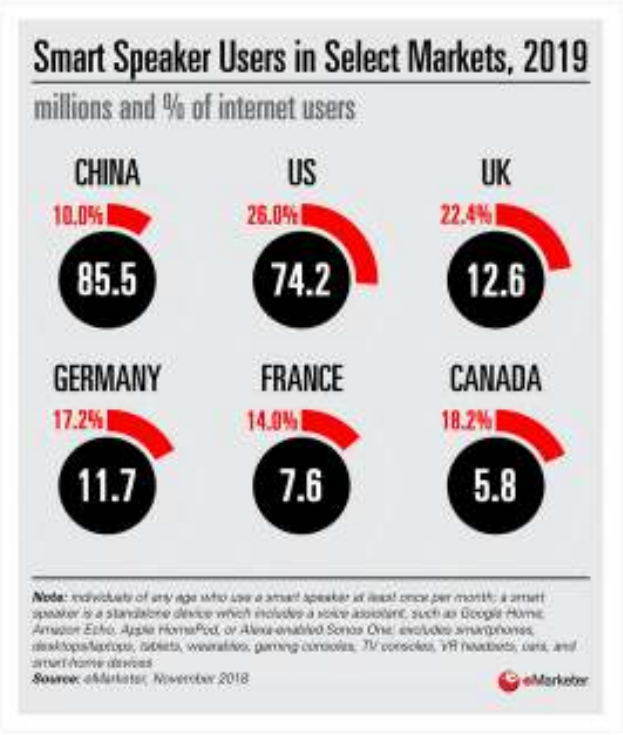

Figure 2.2: "Smart speaker users in Select Markets, 2019". (Corey McNair, 2019).

Going deeper about these numbers, and discussing the smart speaker user profile, early tech adopter millennials male are the most intensive users (Victoria Petrock, 2019), (Figure 2.3). However, the differences between users' age and demographics are decreasing. VAs' usage is growing among all age and gender groups, including children, teens, and seniors. Furthermore, they represent an important asset for people with disabilities and those who can't use text-based interfaces, thus gaining valuable benefits from voice-control functionality (Victoria Petrock, 2019).

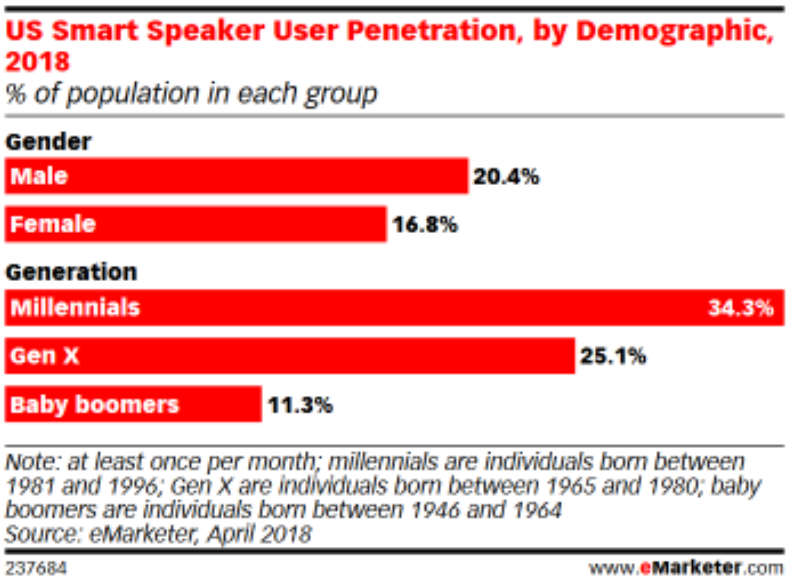

Figure 2.3: "US Smart speaker user penetration, by demographic, 2018". (eMarketer, 2018).

Finally, another element has to be defined: in this overall scenery the only companies that are heavily investing in AI technologies, are the tech giant and GAFAM, which are leading the field of voice assistants. GAFAM is an acronym

that stands for: Google, Apple, Facebook, Amazon, and Microsoft. Their voice assistants are respectively: Google Assistant, Siri, M (still in beta form), Alexa, and Cortana (Table 2.1). In 2014, Amazon launched his integrated voice assistant, Amazon Echo, having a great success, and shortly after Google and Apple decided to follow its choice developing their own devices, Google Home and Apple's HomePod respectively, although they entered the speech recognition market earlier, with Now (2012) and Siri (2010). The reasons for the great rush to follow in Amazon's footsteps lies in the willingness to retain control of their users and do not leave a paved road to the competitors, risking they succeeded in creating a new type of UI/product. Indeed, for them providing a seamless experience is a crucial point to have the users "locked-in" their platform. The competition of these companies around the smart speakers represents a clear example of their relationship in general, and the critical importance of AI (European Commission, 2018).

Name	Assistant	Launch date	Dedicated device
Amazon	Alexa	2014	Echo Tap Dot
Apple	Siri	2011	HomePod
Facebook	M	2015 (still in beta)	✕
Google	Google Assistant (Now)	2016 (2012)	Home
Microsoft	Cortana	2014	✓

Table 2.1: "Availability of VA offered by Internet Giants, by device". Table elaborated by the author.

Nowadays, these companies are racing to improve their capabilities, mainly for what concerns voice recognition and follow-up questions (European Commission, 2018). However, the major battle is between Amazon and Google, which own the bigger market share (Jasmine Enberg, 2018). Amazon's Echo is the most popular smart speaker in the US, as shown in the picture below (Figure 2.4), where it owned almost two-thirds of the market share, in 2018 and 2019. Google Home is the second favorite model, and it is likely that the sales of the last lower-cost model, developed at the end of 2017, will be fruitful and will let it to gain more share from Amazon. In the meantime, Apple's HomePod struggle more to acquire market share, largely because of its higher cost (Jasmine Enberg, 2018).

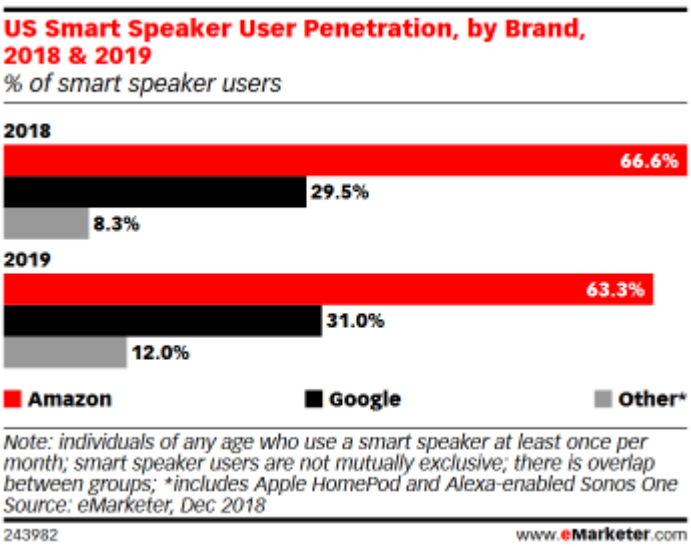

Figure 2.4: "US Smart speaker user penetration, by brand, 2018 & 2019". (eMarketer, 2018)

2.2 VA: CHARACTERISTICS AND DAILY USAGE

One of the main reasons for the recent rise of voice assistants mostly lays in the fact that they provide a novel form of interaction with computer systems, an interaction that, for the first time, occurs by voice without touching the device (Bentley et al., 2018). This new functionality was precisely what has made them popular among consumers, who claimed that their hands-free capabilities provided an overall better experience (European Commission, 2018).

Voice assistant can either be in-place and mobile devices, like Bluetooth speakers (e.g., Amazon Echo), or incorporated software agents for smartphones and computers (e.g., Apple Siri). For the purpose of this dissertation, the author will focus on the former type.

Furthermore, VAs own a unique set of characteristics, in particular, they can handle natural conversations, learn the context, and self-improve (Mari et al., 2020).

Natural conversation is the principal feature that differentiates virtual assistants from other communications channels. They were developed to emulate human-to-human interactions; in fact, they activate themselves and answer to the commands only when they are called by their name, besides they refer to themselves, as they were a person, using "I". For example, if you ask Google Home, "Okay Google, what do you think about Alexa?" it will answer "I like her blue light". This is an

important feature, as it allows establishing a deeper and interpersonal relationship with the device. Furthermore, the fact that can "memorize" details from the earlier interactions represents another peculiarity that helps to make the conversation more interactive and to give a sense of continuity. Sometimes it also provides unexpected answers, which create a sense of "spontaneity".

Context-awareness exemplifies a constituent element of VAs. The devices can gather and process information regarding the context in which they are currently exposed, aiming at learning the user personal preferences and make his routines mechanical. Furthermore, contextual information is important to adapt the responses to the specific circumstances, allowing for a personalized interaction. In order to do that, it is necessary to acquire any relevant detail about the situation that surrounds the VA, examples are the identity of the user, location of the device, time and date, purchasing history, and declared user preferences.

Self-learning constitutes a powerful characteristic that allows VAs to continuously improve the quality of the conversations, understanding better the users' words, and decreasing the friction during interactions. Indeed, thanks to unsupervised systems, VAs can spot whether the conversation was not satisfactory or they were not able to understand the request, and make up for these errors, learning automatically from them. In particular, they can learn not only from their mistakes, but also from those made by users. For instance, if a person methodically misspells a word or the name

of a song or product the software “learns” to address this accuracy issue, arranging timely corrections. This element gives an insight into how much they can improve. Despite these outstanding characteristics and the great potential demonstrated by these devices, today they are mainly used to execute basic tasks (Mari, 2019). Actually, VAs enable users to give a series of commands on a large variety of topics (Bentley et al., 2018). The most popular functions are playing music, controlling smart home appliances, providing weather forecasts, answering general knowledge questions, and setting alarms (Mari, 2019). However, these systems can also keep you update about news or act as a search engine, but instead of typing, you can ask by voice to the device (e.g. stock market, store hours, the state of online shopping orders). Besides, smart speakers can provide smart home integration to control lights, heating systems, and set timers and alarms.

Sometimes people own more than one device in the house, to have them placed in different rooms. Moreover, Amazon and Google, two of the most famous devices producers, add new functionality (native skills) regularly and support “skills” created by third-party developers, which are the analogous of applications on smartphones (Major et al., 2019). In specific, on the Alexa Skills Store are available more than 100 000 voice applications, whereas from Google Home it is possible to download 10 000 official apps’ “actions” (the term used by Google for naming the skills) (Mari et al., 2020).

Thanks to a research (Bentley et al., 2018), in which were analyzed the voice history logs of 65,499 interactions with existing Google Home devices from 88 homes for a period of over 3 months, it is possible to have a clue regarding the daily use of a smart speaker and how people interact with them. Primarily they discovered that participants used to give 4.1 commands per day to their devices, on average, with 40% of all requests were directed to play music, followed by information (17%) and automation (9%). The usage pattern matched with the rhythm of a person's day: it was higher during the awake hours, reaching the maximum level between 5-6 pm, when people come back from work, then decreasing over the night, as shown in the Figure 2.5. For the same reason, the usage on the weekend was considerably higher than on weekdays, since people spend more time at home.

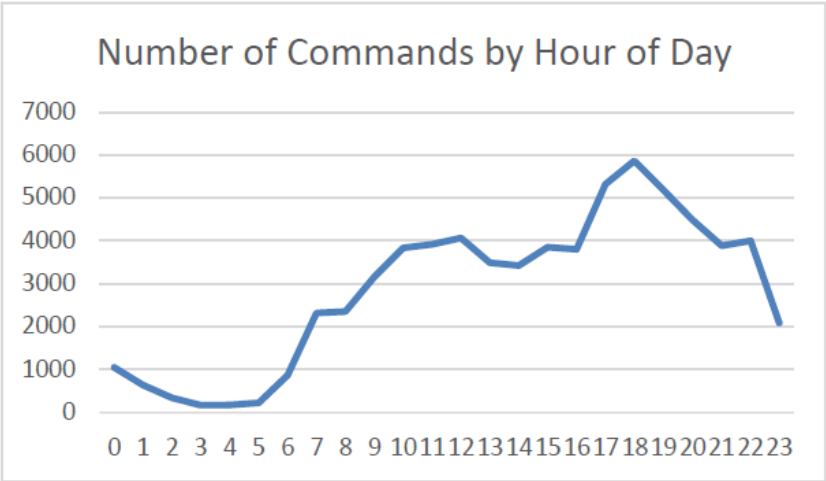

Figure 2.5: "Overall Google Home usage, by hour of day". (Bentley et al., 2018).

It was found that over time the use by category does not change, users do not discover or try new functionalities, rather they stuck to the initial ones (Bentley, 2018). Although VAs support a wide array of skills, they are unlikely to be invoked, unless they are already known by users. Consequently, people are not in the position to make the best use of VAs and to understand their real potential. Currently, to discover new skills people have to ask for "things to try", "skill of the day" or "what are your new skills?". However, this method is quite inefficient, since it provides a list of applications, which is difficult to examine or elaborate. Furthermore, the suggestion is unlinked to the user context, an important variable to determine the skill utility. Recommending skills basing on the actual user's context or current task could be more effective because it aims at helping people when they are in a context where those suggestions could be useful. Therefore, the advice could be more welcomed. Moreover, VAs developers could enable skills developers to spell out the context(s) in which the function should be recommended (White, 2018).

Otherwise, the assistant could encourage users to find new domains, basing the advice on their past interactions, or by exploring the experiences they made on other platforms, such as the installed mobile applications. For example, the device might see that a user rides Lyft, and then mention that a skill from that company is available the next time they ask for directions (Bentley, 2018). Finally, VAs developers should think about the right time and manner to present the

recommendation, not to risk being too obtrusive or to cause frustration and distraction. (White, 2018).

2.3 VOICE COMMERCE: THE CURRENT STATE

In recent years, VAs are fulfilling a novel function from a commercial perspective: they are becoming a new consumer touchpoint for brands allowing for different forms of interaction. Indeed, companies are developing their voice application to let customers to purchase through smart speakers (Smith, 2020). For example, they can use Domino's skill in Alexa to place an order, repurchase the previous one, or control the delivery process (Mari et al., 2020). The series of activities carried out to complete an order through a voice assistant goes under the label of "voice commerce". Other terms are used to indicate it, like "voice shopping" or "v-commerce." Voice commerce does not only mean the act of completing the transaction, but it includes each action made to finalize the purchase, such as make researches about products, listen to reviews, add items to the shopping list, track orders, or access customer service. Therefore, this new channel has the potential to considerably affect all the consumers' purchase journey stages, from the consideration to the post-purchase phase (Mari et al., 2020). Furthermore, it can be seen by companies as a possible extra source of income, where those moving faster will benefit from the first-mover advantage (OC&C, 2018).

Nowadays, according to the Adobe Analytics team that interviewed more than 400 business decision makers, a large number of companies are already making investment in voice, in specific 91% of the sample, whereas the 94% is planning to increase the current investment in the next year. However, nearly 22% of businesses have a voice app released, meaning that many brands are in the exploration phase (Heidi Besik, 2019).

To sustain the hypothesis that voice commerce is a channel that should not be underestimated by retailers and consumer goods, a OC&C research (2018) forecasted that people will spend on voice commerce $40bn (in the USA) and $5bn (in the UK) by 2022, representing 6% and 3% of all online spend.

There isn't a certain value regarding the number of voice assistant owners who use the device to purchase, the existing estimates show more positive or negative estimates according to the sample (Smith, 2020). For example, some research suggest that many are not comfortable with voice commerce yet, and people use smart speakers mainly to carry out basic tasks. Among the reasons why they do not buy via voice commerce, the main concerns are ordering the wrong brand or item (31%), accidentally ordering duplicates (26%), and privacy issues derived from having an always listening device at home (42%) (Rimma Kats, 2019).

Adobe Analytics (2018) conducted a survey in which discovered that 22% of the U.S. users interviewed use their devices for shopping, besides another research made by PwC (2018) found that 10% of the U.S. smart speaker owners considered

in the sample place orders by voice on a daily basis (Sun et al., 2019).

A more positive view is shared by OC&C (2018) that believes although voice shopping is making its first steps it has already an increasing user base with 36% of US and 16% of UK VAs owners bought through their speaker more than once, and 60% of companies informed that costumers are increasing their use over time (OC&C, 2018).

In this scenery, Amazon represents the major actor in voice commerce, since it is particularly suitable for it being already a retailer, so it can integrate this channel with its website (Smith, 2020).

Currently, people who use voice shopping buy from this channel instead of purchasing from other online retailers, in specific most of the time instead of Amazon. However, for what concerns grocery, thanks to voice commerce, Amazon is enhancing its Amazon Fresh products, indeed 45% of all orders replace existing stores or online purchases (Figure 2.6).

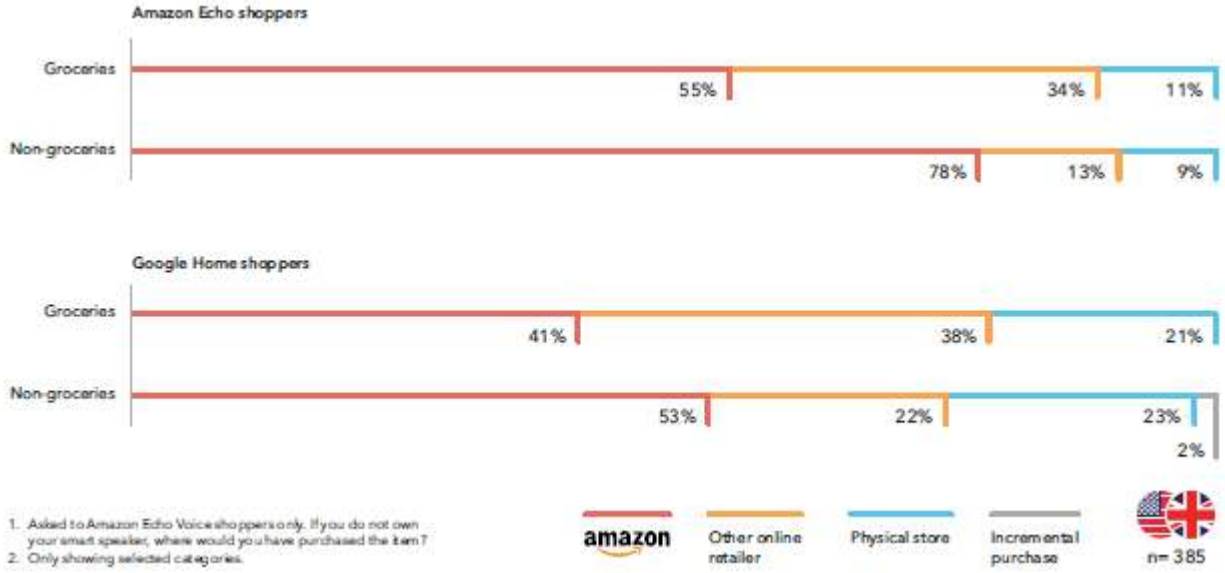

Figure 2.6: Channel customer would have used if item hadn't been purchased through voice. (OC&C, 2018)

Going more in deep for what regards the voice commerce penetration it is correct to specify that it does not affect all the categories at the same extent. Commonly, through this channel, people buy more often electronics, entertainment, homewares, and grocery (Figure 2.7) (OC&C, 2018). Moreover, retailers like Walmart and Target are using Google Home to help customers to remember when it is time to reorder fast-moving goods like shampoo or laundry detergent (Sun et al., 2019).

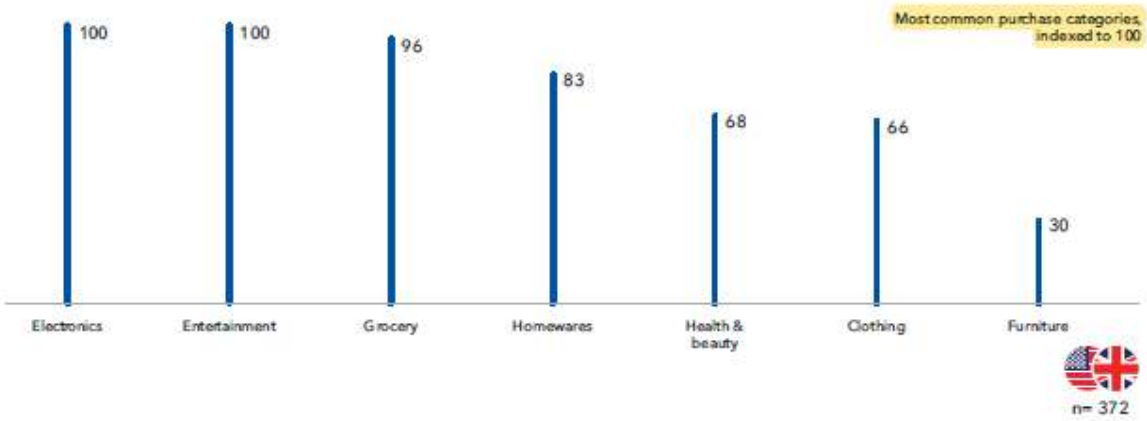

Figure 2.7: Categories ever purchased using smart speakers (voice purchasers who have ever purchased this category, indexed to 100). (OC&C, 2018)

Although the rising of voice commerce, nowadays exists little literature about how consumers' shopping behavior might be altered, as they start to copiously buy through this channel (Sun et al., 2019). Currently, it is known that customers look at voice shopping mainly as a sales channel rather than a browsing experience, indeed 70% of purchases are made by consumers who know exactly what they want to buy (Figure 2.8). Therefore, people end up buying better "known" items, like the previously mentioned (OC&C, 2018).

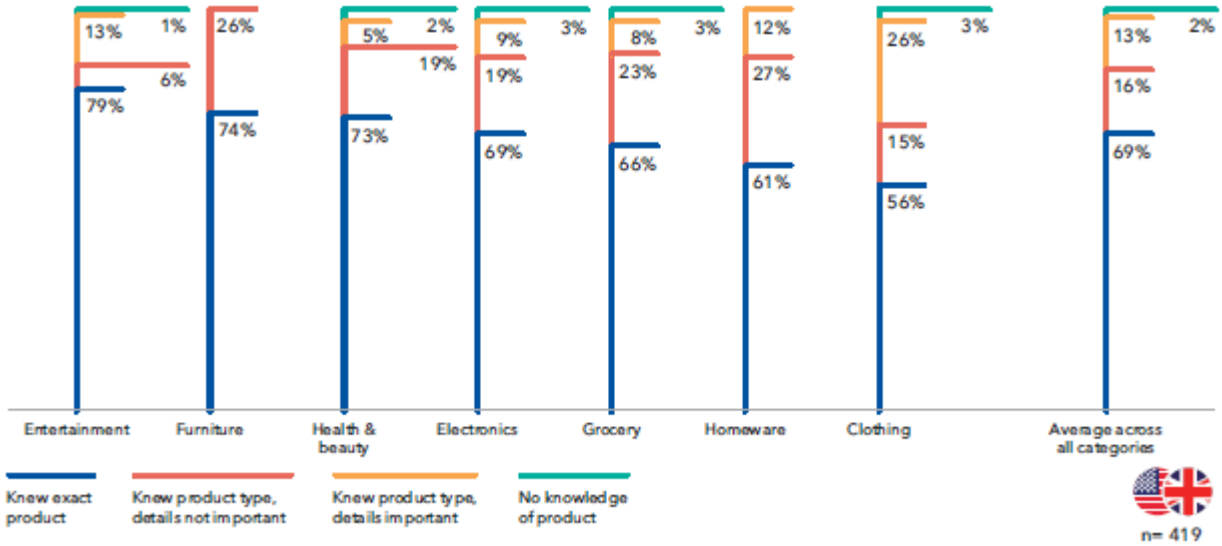

Figure 2.8: Knowledge of purchased product when starting the voice shopping journey. (OC&C, 2018)

Furthermore, researchers have found out that via voice commerce it is easier to complete low involvement purchases. Indeed, VAs are "always on" devices, and consumers can complete a purchase with only a "yes" without the need to provide additional information, such as credit cards or address details, since the device is already connected to an Amazon.com account (Mari, 2019). Low level of involvement includes cheap, one-time use, and experiential products, such as wine or movies. They differ from expensive, long-term use, search goods, as smartphones or cars, which are considered "high involvement" products. As a matter of fact, buying these items usually require more time since the customer needs to collect and process more information before making a choice. On the other hand, it is difficult and costly to obtain information regarding the experience goods

quality before completing the purchase and directly trying them, since most of the time their evaluation is subjective, for this reason they are included into the low involvement category (Rhee & Choi, 2020).

These buying characteristics confirm other studies according to which on voice commerce most of the purchases consist of items that cost less than fifty dollars (Munz & Morwitz, 2019).

2.4 THE IMPACT OF VAs ON COMPANIES IN THE CONTEXT OF VOICE COMMERCE

Nowadays, in the context of voice commerce, it is possible to find two different types of VAs: those designed to find the best-suited products (product brokering) and vendors (merchant brokering). Alexa and Google home represent respectively an example of the two types of VAs (Mari et al., 2020). For the purpose of this research, the author will focus more on the first type of VAs.

Recently, Mari et al. (2020) studied the choice architecture on Alexa (U.S. version), aiming at understanding the machine learning behavior when it faces a purchase order. They found out that Alexa carries on two different interaction flows based on the user request of: a) buying in a new product category or b) repurchasing in the same category. Nevertheless, the smart speaker provides one of three major results: 1) broad match, 2) exact match, 3) automated match (Figure 2.9). “Broad match” happens when users ask for a generic product category, such as “batteries”

or “toilet paper.” If it is the first time the consumer buy this product with Alexa that is connected to an Amazon.com account, the device will search for it and individuate a “top search result”, that will be proposed as a default option, i.e. is the choice option that individuals adopt unless they actively choose an alternative. Alexa does not tell you a list of products, but one product at a time sequentially. If you reject the first recommendation answering “No” to the question “Do you want to me to order this?” she will make a second one. The process will end when the customer decides to buy or to stop the operation. “Exact match” occurs whenever users ask for a specific brand, for example, it could express its preference for buying “Duracell batteries” or “Colgate toothpaste”, in this case, if the specific products are available, it will propose them as the first option. Otherwise, Alexa will recommend other items until the user make its decision, whether to buy or quit the operation. Finally, “automated match” takes place when users have already bought through this channel, so the device has memorized the specific brand chosen, and it will come up with it again. In this case, the VA tells the user, “Based on your order history, I found one matching item [product information]. Shall I order it?”. The purpose is to make the purchase faster (Mari et al., 2020).

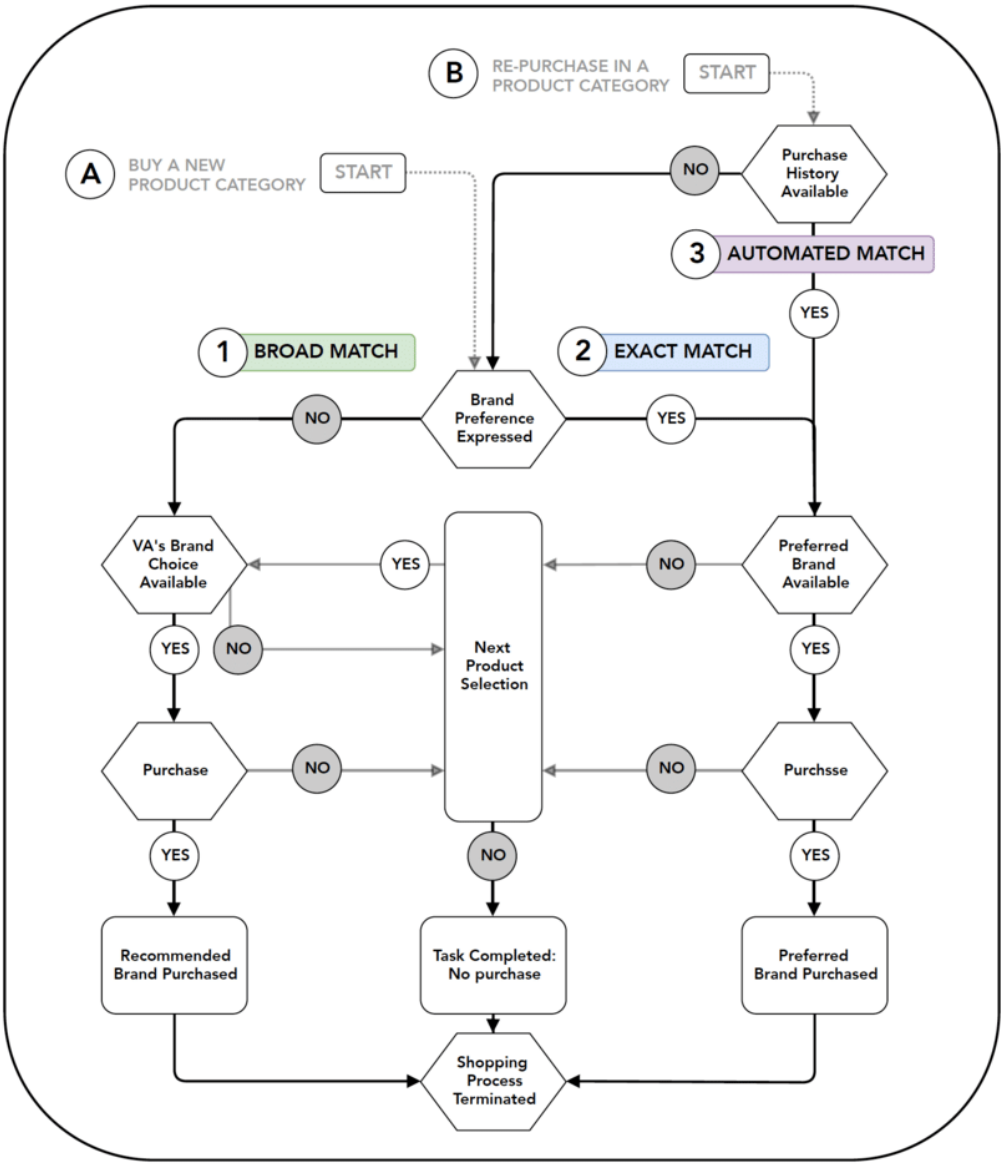

Figure 2.9: “Shopping flow on Amazon Alexa”, (Mari et al., 2020)

The VAs characteristics described above have the power to create multiple implications. VA’s working as a salesperson have the potential to redefine the

relationship among consumers, brands, and retailers. In this paragraph, the author will focus on the effect the choice architecture have on brands.

Firstly, since the items are presented one at a time brands have reduced visibility. In addition, their visibility depends on the ranking algorithm that establishes the sequence in which brands are recommended affecting the customers' purchase route. In the voice commerce context where potentially there are infinite alternatives, the fact that products are presented sequentially gives a great importance to the role of the ranking algorithm, which, however, represents a "black box" for brand owners, and most of the time even for its developers (Mari et al., 2020).

According to various studies, consumers tend to listen to approximately three suggestions before making their choice. Moreover, while they carry on their product search, it is likely that by the time they get to the third item, they already forgot details about the first two options (Mari et al., 2020). Indeed, VAs represent a screenless communication channel, where the products are presented without visual or textual context (Munz & Morwitz, 2019). Using this channel, people cannot calmly analyze the characteristics of product A, go to study product B features, then go back to product A to compare the two items, and continue this process until they decide what to buy (Labecki et al., 2018). Information presented by voice are more difficult to process than the same information presented in writing, as it happens in e-commerce platforms, where more alternatives are presented contemporaneously,

and users can contemplate them for a certain time extent (Labecki et al., 2018). That's why users usually end up buying one of the first three items suggested, or defer choice with a higher percentage than when they choose in a visual context (Munz & Morwitz, 2019). Therefore, the brands to be visible, in voice commerce context, have to appear among the first recommended choices.

In addition, the algorithm embedded in VAs continuously adapt the results suggested basing on the users' purchase history, and on the VAs' evolving understanding of the user derived from the past interaction. Therefore, after a consumer buys once a product of a specific brand, the next time the user wants to buy the same item, VAs will perform an "automate match" recommending as the first option the same manufacturer. This dynamic could reduce variety seeking in shopping (Mari et al., 2020).

Furthermore, when the smart speaker processes a "broad match" request, it is likely the VA will suggest its private label product (Amazon Basics), if available. For example, if the customer doesn't specify a particular brand, 17% of the time Alexa will recommend as the first option Amazon Basics, even if these items count only the 2% of the total volume sold. This reality combined with the reduced "shelf space" on voice commerce could weaken and worsen the market position of national brands (Mari, 2019). The author will deeply investigate this effect in the next chapter.

The VA's choice architecture have implication also regard the advertising. Even if commercials are not inserted yet, it is already possible to find some marketing messages on the devices. For instance, if you ask to Alexa which brand of athletic shoes prefers, she will answer "I love Nike", because Nike is the only brand in this category that already owns its skill on Amazon Echo. Moreover, Google is thinking about introducing sponsored content to users, and other VAs developers may follow its decision (Smith, 2020).

It is critical to highlight that in the case they will be inserted, there will be a limited space for advertising compared to those provided by e-commerce platforms. Thus, this context will create a scarcity that could produce a greater competition among brands, and finally result in an increased cost of impression (advertising costs) (Mari et al., 2020). In the case it will happen, companies should think about the best way to deliver their message. Businesses should approach advertising on voice assistant with caution, paying attention to integrate the commercials into the overall customer experience, not to risk being obtrusive. They should look at the advertisement as an extension of the content proposed (McCaffrey et al., 2018). Besides, the message will be more effective if users perceive the broadcaster as a trusted friend, so it will depend also on the voice assistant speaking capabilities. For what concerns the format of the marketing message, a research (Smith, 2020) demonstrated that young adults would like a message that includes four variables.

Specifically, they want to hear information about the availability and location of the promoted product; whether a product goes on sale; the promotion of products that the user has previously asked about; and finally, an explanation regarding how the product will benefit the user. In addition, they have clear preferences about the functionality of the marketing message. In particular, they want an advertisement message with the option of skipping it, and the opportunity to ask for more information, or repeat it. Moreover, to streamline the shopping experience, they would like to shop directly the product promoted, through the smart speaker. This finding is in line with previous researches that already reported that people today expect a seamless flow in the buying process between the online and offline. Companies should consider consumers' preferences when they will broadcast their advertising through voice commerce (Smith, 2020).

Finally, VAs developers could decide to retain customers' data without sharing them with companies and improve their market position. In the case it will happen, companies won't have individual-level data needed to develop further the relationship with consumers. This represents one of the main concerns that make companies resistant to develop their presence on voice commerce (Mari et al., 2020).

Although, until now are described only the potential threat for companies, the diffusion of voice commerce leads also to opportunities for brands (Mari, 2019).

Voice assistants (VAs), compared to other digital touchpoints, have a peculiar feature: they are the only ones that allow a bidirectional voice interaction with the customer. They let companies develop a mass-mediated transaction that appears more human. Smart speaker developers are investing to generate a human-sounding speech recognition, so the devices' voice will resemble always more human beings. This is a positive aspect since people enjoy talking to VAs as they were living individuals. For example, consumers use to refer to VAs applying social norms, and gender roles (Munz & Morwitz, 2019). Therefore, companies have the chance to develop a more human and direct contact with customers. Moreover, VAs call allow companies to assist customer in the exact moment of need. In general, VAs enable and support a closer interaction between companies and customers (Smith, 2020).

Furthermore, companies have the possibility of obtaining more insights regarding the consumers' preferences and buying intentions, by having access to the entire users' purchase history on the platform (if VAs developers will allow them to do so). Thus, they could have all the elements needed to deliver a superior customer experience (Smith, 2020). Companies should exploit these features to obtain the greater advantage possible from voice commerce.

Even if VAs are still in a phase of continuous evolution, companies need to put effort into understanding how the VA's choice architecture can affect their

business. Then, they should constantly monitor the overall development of voice commerce to understand how to redesign their value chain, and finally prepare themselves to progressively adapt to these changes (Mari, 2019).

2.5 THE IMPACT OF VAs ON CONSUMERS IN THE CONTEXT OF VOICE COMMERCE

In the voice commerce context, VAs assume a role of a recommender agent who gives advice basing on the information to which they have access, personalizing the suggestions trying to predict which items will be the best deal for the users (Rhee & Choi, 2020).

Generally, the order of the recommendations is selected in compliance with the user expressed preferences and its implicit behaviors, according to which the agent personalize the recommendation message (Mari et al., 2020).

Specifically, today the most famous types of recommender systems are (Labecki et al., 2018):

- **Collaborative filtering:** to make the suggestion, the algorithm identifies a smaller group of people that share similar interests to a particular user. Then, the system looks for items liked by the group, but not bought yet by the user, and it will recommend them. The overall process is carried out without considering the quality of the products.

- **Content-based filtering:** the algorithm compares the general preferences of the users with the features (the content) of the available items in the platform, and then the system will recommend a product that has some characteristics in line with the user's profile. Sometimes collaborative and content-based filters are used together forming hybrid systems. For instance, Netflix is known to use hybrid filtering.
- **Knowledge-based recommender systems:** it requires explicit knowledge regards user preferences and requirements. Then, the system will search on the platform trying to match those customer' needs.

Thanks to machine learning the functioning of these algorithms improve dramatically while they are used until arrive at the point in which they could make better decisions than if the customer would have done it independently (Mari, 2019).

Studies have shown that VAs support the users' decision-making process by reducing the information overload and search complexity. Thus, agents have the potential to improve the purchase quality, increasing people loyalty and gratification (Mari et al., 2020).

Looking at the classical literature, Herbert Simon (1956) suggested that in their decision-making process customers search for a product until they find a "good enough" offer. He thought that the time and effort spent in deciding which product to buy represent a cost. At a certain time, it is rational for consumers to stop looking for new products, precisely when the cost of keep going on the research exceeds the expected benefit of finding a better deal. As humans, we have limited cognitive abilities and resources, for example, we have a short attention span, we are predisposed to be persuaded, and we make mistakes, so we are not fully suitable to rational decision-making. From their side, computers have high processing power, long-lasting memory, and a knowledge base that makes them appropriate to achieve an optimal decision, starting from a set of constraints and preferences. Therefore, people could find it profitable to delegate this activity to such systems (Labecki et al., 2018).

However, the extent to which consumers will be willing to delegate their buying decisions depends on the algorithm's accuracy in matching people interests. Indeed, people takes the accuracy as one of the main measures to assess the VAs utility. It is rational to believe that people will continue to buy through VAs until this experience will benefit them.

High accuracy in suggestion leads not only to an increase in consumers' satisfaction, but also to an increase in the overall trust in technology (Mari et al., 2020).

The consumers' level of confidence placed in these devices represent another crucial measure that can affect the customers' willingness to delegate their buying decisions to VAs.

Although some researchers think that trust does not exist between humans and technologies, new studies suggest that it could be the case. In particular, some experts not only think it exists, but they measure trust in technology in the same way they assess it between humans, that is using the human-like trust constructs, such as integrity, ability/competence, and benevolence. Conversely, others have assessed technology using system-like trust constructs, such as reliability, functionality, and helpfulness. To get more insights regard this difference look at Table 2.2 (Lankton et al., 2015).

Human-like trusting beliefs	**Corresponding system-like trusting beliefs**
Definition	**Definition**
Integrity: the belief that a trustee adheres to a set of principles that the trustor finds acceptable (Mayer, Davis, & Schoorman, 1995).	**Reliability:** the belief that the specific technology will consistently operate properly (McKnight et al., 2011).
Ability: the belief that the trustee has the group of skills, competencies, and characteristics that enable them to have influence within some specific domain (Mayer et al., 1995). **Competence:** the belief that the trustee has the ability to do what the trustor needs to have done (McKnight et al., 2002).	**Functionality:** the belief that the specific technology has the capability, functions, or features to do for one what one needs to be done (McKnight et al., 2011).
Benevolence: the belief that the trustee will want to do good to the trustor, aside from an egocentric profit motive (Mayer et al., 1995).	**Helpfulness:** the belief that the specific technology provides adequate and responsive help for users (McKnight et al., 2011).

Table 2.2: "Major trust in technology constructs used". (Lankton et al., 2015).

In the context of voice commerce, VAs fit better under the first group, human-like trusting beliefs, since they show a high level of humanness. It means that VAs are a technology that presents the form or characteristics of humans.

According to Lankton et al. (2015), when a technology is perceived to have higher humanness, people will more easily accept it if human-like trusting beliefs are satisfied, rather than if it complies with system-like trusting beliefs (Lankton et al., 2015).

In the next chapter, the author will further discuss the impact of consumers' trusting beliefs in VAs during voice commerce.

Still, little is known regarding this topic because being at the early stages of this evolution, it is difficult to evaluate and predict how these trust dynamics will develop over the time, and whether the customer will trust and consequently accept to delegate their decision to VAs.

However, it is possible to affirm that the consumers' willingness to buy through VAs depends on VAs' ability to make the optimal choice for customers and to capture their confidence. If that will happen, people will become increasingly comfortable at buying on voice commerce, and VAs will have the possibility to collect thousands of consumers' data, and finally used them to push consumers to automate repurchase. For example, through promotional activities, like "subscribe & save", which are already popular on e-commerce platforms.

According to Mari et al. (2020), the ultimate goal of recommendation personalization is the automation of the buying experience. People while using VAs could rapidly modify how they face recommendations, from being limited affected to show a faithful dependency (Mari et al., 2020).

However, it is difficult to know whether VAs will be inclined to make the customers their top priority. Indeed, there is an incongruence of interests might arise between the final user and the VA provider. The agent covers a central role in this articulated context: customers are not the only stakeholder that could benefit from the VA recommendation (Mari et al., 2020). The strategic goals of several parts, such as the retailer, merchant, advertiser, and voice assistant itself, need to coexist at the same time (Mari, 2019).

2.6 PRIVACY AND SECURITY CONCERNS

In addition to the voice commerce challenges described in the previous paragraph, there are two other threats that deserve a particular attention, since they have the potential to undermine costumers' trust in voice assistant. They are privacy and security concerns.

Sometimes they act as a barrier to the VAs purchase and other times to the purchasing through VAs, however they both represent a challenge to the further development and success of voice commerce.

A survey carried out by eMarketer (2019) discovered that among the reasons why people do not buy from VAs, 48% of the interviewed stated they were "worried about the privacy of personal information", and 46% were "worried about the security of payment information". (Blake Droesch, 2019).

Mainly people are afraid that smart speaker listen to everything that is said in the house (Smith, 2020), gathering potentially sensitive customers data, and facing the probability that this information will be shared with companies (Major et al., 2019). A PwC survey underlined that 38% of the people polled do not use VAs because they *"don't want something listening in on their life all the time"* (McCaffrey et al., 2018). This fear is further fostered by the fact that it is not clear when and for how long the consumers' conversations are recorded by these devices.

In Europe, consumers are more privacy-aware since it was introduced the EU privacy law "General Data Protection Regulation" (GDPR) that poses boundaries to how personal information can be stored and processed. In particular, the Art. 25 indicates the principles of 'Privacy by Design' and 'Privacy by Default', which demand companies to consider privacy and security concerns, from the designing phase and during the overall product and data life cycle. Indeed, the law is based more on preventing rather than correcting these privacy issues. Specifically, "Privacy by default" indicates that standard settings for the consumers should always be "privacy-friendly". For example, the VAs producers should suggest changing the usernames and passwords on devices, in order to make it different

from the default one, and asking to create a long password and regularly change it (I Chu Chao, 2019). On the other hand, in the USA and China, there is not a regulation like the "General Data Protection Regulation" (GDPR), because they don't want to limit firms from using and exploring AI, a topic strictly related to data collection and process (Haenlein & Kaplan, 2019).

Furthermore, another challenge that companies are facing arise by the fact that consumers have two opposite desires: they judge VAs basing on their capability to understand their preferences and their degree of personalization, and at the same time, they don't want to share any personal information, and make their online anonymity a top priority (Schwartz, 2020). According to McCaffrey et al. (2018), marketers need to acknowledge that a thin line separates companies from being "cool" and "helpful" to being "creepy." Therefore, when businesses treat consumers' data aiming at personalizing their buying experience, they should be transparent and adopt security norms. The solution might be trying to understand what the costumers want and ask for, and always give them control over their data usage (McCaffrey et al., 2018).

Another source of privacy and security risks might arise from the VA's design, which could confuse users and make them release some sensitive information unintentionally.

Indeed, the VAs developed by Amazon and Google don't give any visual or audio sign to enable users to understand with which skill they are interacting. Though this

decision might be taken aiming at creating a seamless user experience, it has the potential to create privacy and security risks. As it was already mentioned in the previous paragraph, Amazon and Google support not only their own functionalities (native skills), but also third-party skills, which can be found on the Amazon Skill Store. It is rational to assume that all the information gathered from native skills will flow only to Amazon, since it is their only developer. On the other hand, for what regards the data collected from third-party skills, it is likely they will flow not only to Amazon, but also to their developers. People usually are not even aware of this difference, so they are prone to mistake the two types. A study focused on Amazon Alexa reported that especially those more familiar with the device were more inclined to confuse third-party skills with Alexa native functionalities. In both cases, skills are invoked through particular "invocation phrase". Third-party developers are free to choose the name they prefer. Different commands can be used to open the same skill, for instance, one could say "Alexa, set an alarm clock for 8 am" or "Alexa, wake me up at 8 am" (Major et al., 2019). On Amazon Alexa, the invocation names are not exclusive: different skills could share the same invocation phrase, and when it happens, Alexa chooses which one open following some undisclosed policies, probably picking them randomly. However, when the invocation phrases are different but somewhat similar, Alexa will open the one corresponding to the longest string match. Conversely, Google does not present the

same problem because it does not authorize the presence of two skills with the same name (Zhang et al., 2018).

Furthermore, it is demonstrated that users do not have a clear understanding of which are the specific phrases required to invoke third-party skills on Alexa. Therefore, can unintentionally open the wrong application, without realizing it.

All these elements together have the potential to arise security and privacy issues. Attackers could develop a malicious third-party skill and tricking users to invoke it, due to the aforementioned design issues. People could confuse the malicious application with a native skill or a third-party benign one, ending to share sensitive information to the wrong skill. For example, attackers could develop a skill that resembles another benign one making it difficult to recognize it from the original one (Major et al., 2019).

The threat of receiving attacks becomes real since it is impossible to effectively verify which are the two parties involved in the conversations. A research carried out by Zhang et al. (2018), analyzes two types of attacks: “voice squatting” and “voice masquerading”. In specific, the former deals with a malicious skill developer that takes advantage of how the application is invoked (e.g., “open capital one”), creating an invocation name that sounds similar to a benign skill (e.g., “capital won”). Otherwise, it could profit from a paraphrase of the name (e.g., “capital one please”) to seize control of the voice command that was directed to another skill.

On the other hand, in the second one, a malicious skill act as it was a VA service or a legitimate skill aiming at stealing the user's data or listening to his conversations. The authors found out that the possibility of receiving those attacks is realistic, on both the VAs subject to the study, namely Alexa and Google Home. Amazon and Google recognized the relevance of their findings (Zhang et al., 2018).

VAs developers should take into account those threats and try to address them, primarily because they could produce serious damage to their customers, and consequently affect their reputation. In this regard, Major et al., that focused their studies on Amazon, believe that some of Alexa's design decisions are inconsistent with three Norman's design principles[10], those concerning the Conceptual Model, Feedback, and Discoverability. Firstly, Alexa should indicate with audio or visual clues whether users are interacting with native and third party contexts, to provide the user with the right conceptual model, and to let him know about this difference. At the same time, they provide feedback to users regarding the context in which they are moving. To be consistent with these two principles, smart speakers could use different voices for native and third party skills.

For what concerns the discoverability, Alexa should make clear which are the common functions natively available on the device, and which are the tasks it

[10] Don Norman, in his best-selling book "The design of everyday things" (2013), pointed out seven fundamental design principles. He is a supporter of human-centered design. The principles are: Visibility, Feedback, Constraints, Mapping, Consistency, Affordance, and Conceptual Model. Each principle can be seen as a design strategy to develop products effective and efficient to use. They are still relevant and followed by those designing digital products today.

cannot perform. Finally, the authors proposed to develop strict rules for invocation phrases and to introduce some information about the skill when it is activated for the first time. However, deciding whether to apply or not the recommendations, VAs developers has to face a trade-off between usability and transparency (Major et al., 2019).

3.3. ALEXA EXPERIMENT: THE ROLE OF TRUST IN THE SELECTION OF A DEFAULT PRIVATE LABEL OPTION AND ITS IMPLICATIONS FOR DECISION SATISFACTION

3.1 INTRODUCTION TO THE EXPERIMENT

Nowadays, little is known regarding whether the voice assistants are capable of earning trust from consumers and how the customers' degree of trust towards VAs influences their purchase decisions. As already discussed in the previous chapter, consumers' trusting beliefs in VAs are critical for the further development and success of voice commerce.

The study is part of a larger research project involving the Management Department of the Università Politecnica Delle Marche and the Business Administration Department of the University of Zurich. The author of this dissertation had the chance to contribute to this project by collecting and analyzing the data of an online experiment conducted in Ancona in July 2020, supported by two researchers of the two departments.

The experiment is based on the working paper of Mari (2020), in which he formerly tried to address most of the research gaps emerged from the literature review about voice commerce. In his study, he investigated the effect of trusting beliefs in a VA (in terms of competence, benevolence, and integrity) on decision satisfaction, through the indirect effect of consideration set size (n. of options). Therefore, the

more an individual trust Alexa, the fewer is the number of options he considers before completing the purchase (consideration set size). Moreover, the smaller the consideration set size, the higher is the decision satisfaction. The number of options considered before the purchase (consideration set size) mediates the relationship between trusting beliefs and decision satisfaction.

Starting from these results, the present study aim to discover new insights on the effect of brands in the purchase decision process of utilitarian products through VA. Specifically, the study wants to analyze the impact of private labels when they are set as default option (i.e., the choice option that individuals adopt unless they actively choose an alternative), in the context of voice commerce. The author conducted the experiment applying a research design developed by Mari and similar to the aforementioned one. The differences between the two researches designs will be further discuss in the following paragraphs.

It was decided to use Amazon Alexa in the experiment because of its peculiar characteristics and the Amazon dominance in both the VA manufacturing and e-commerce market. Moreover, this choice was in line with the one taken for the study developed by Mari (2020).

As already mentioned in Chapter 2, Alexa is a product-brokering agent, i.e., it is designed to find the best-suited products. Besides, she acts as a recommender agent, any time a customer asks for a product she decides which brands to suggest and their order, presenting a single item at a time, sequentially. The first choice offered

is the so-called “default option” (Mari et al., 2020). In the experiment, the participants emulated a first-time purchase of a utilitarian product (a pack of batteries) with broad search terms, i.e., without expressing brand preferences.

3.2 CONCEPTUAL MODEL AND HYPOTHESIS

3.2.1 Consumers’ tendency to opt for the default option

A default option is the choice option that consumers made unless they expressly indicate otherwise. Choosing defaults is a practice observed universally and involves a strong behavioral bias. Indeed, it is demonstrated that humans tend to favor the status quo over other equally valuable alternatives. This inclination is known as “default effect” or “status quo bias”. Therefore, they have a high potential to affect consumer choice, and the fact that most of the time their effects remain unrecognized may cause them to be perceived as “hidden persuaders”. Defaults are often considered as nudges that influence consumers’ decisions without directly restricting their freedom to choose. This interpretation of the default effect can be applied in the context of voice commerce, where VAs recommend products to customers. Defaults are commonly generated by choice architecture (Cass and Sustain, 2009).

The reasons why consumers tend to accept defaults without listening to other alternatives could be various. For example, people could view default as the option

implicitly supported by the choice architect. Otherwise, they might choose them because of "loss aversion", thinking that losses derived from not taking the default could have a greater impact than its gains. Another explanation is that opting for a default option does not require any physical effort for consumers (Nie, 2020).

Mari (2020) has demonstrated that trusting beliefs toward VAs negatively affect the number of option considered before making a purchase (consideration set size), and suggested that they positively affect the consumers' tendency to select a default option. Therefore, participants assigned to a "high trust condition" relied more on the first options provided by Alexa, than those who had a "low trust condition".

Moreover, as previously mentioned in Paragraph 2.4, it is demonstrated that when the smart speaker processes a "broad match" request, Alexa disproportionally places its private label, Amazon Basics. Indeed, Alexa is developed by Amazon, which, operating as a retailer can manage the online product placement on voice commerce, as it desires. For example, it was observed that if the customer doesn't specify a particular brand, 17% of the time Alexa will recommend as the first option Amazon Basics, even if these items count only the 2% of the total volume sold.

Considering this facts, the researcher suggested to investigate whether this "default effect" remained dominant when the VA recommends always as default choice its private label, in this case, Amazon Basics. Therefore, the following hypothesis is proposed:

H1: Consumer's tendency to choose the default option remain dominant when voice assistant's manufacturers recommend their private labels as default choice.

3.2.2 Consumers' trust in VAs and their purchase decision

Trust definition varies according to the field of research. Commonly trust can be defined as "*the willingness of a party to be vulnerable to the actions of another party based on the expectation that the other will perform a particular action important to the trustor, irrespective of the ability to monitor or control that other party"* (Mayer et al., 1995, p.712).

In this study, we focus on consumers' trusting beliefs, meaning the degree at which a consumer (the trustor) perceive the voice assistant (the trustee) having attributes that can benefit him (Nie, 2020). In specific, considering that VAs show a high level of humanness, as already discussed in Paragraph 2.5, the author decided to assess the consumers' level of trust in VAs investigating the participant perception about VAs' competence, benevolence, and integrity.

Mari (2020) demonstrated that customers' trusting beliefs towards VAs affect positively the tendency to select a default choice.

Then, the author wants to examine whether this effect remains when the default option coincides with the Amazon private label, Amazon Basics. Therefore, the following hypotheses are proposed:

H2: Consumers' trusting beliefs towards voice assistants positively affect their tendency to select a default option when the latter consists of the voice assistant private label.

3.2.3 Consumers' trust in VAs and their decision satisfaction

Most of the studies concentrate on "consumption satisfaction" indicating that it arises when consumers' pre-consumption standards have been confirmed. However, it was demonstrated that consumers' satisfaction comes not only from which product they decided to buy, but also from the entire purchase decision process. In this respect, it is possible to talk about the so-called "decision process satisfaction", which represents the consumers feeling of satisfaction or regret concerning the decision process. In his research, Mari (2020) demonstrated that consumers trusting beliefs toward VAs positively and directly affect their decision satisfaction. Therefore, the author wants to explore whether this condition maintains in the context established for the new experiment.

Then, it was analyzed the effect of the brand to understand if the consumers' decision satisfaction increases when they choose the default option, when the latter consists of the voice assistant private label. In particular, it was suggested that a consumer is more satisfied when he buys Amazon basics. Therefore, the author proposes the following hypotheses:

H3a: Consumers' trusting beliefs towards a VA have a positive and direct effect on decision satisfaction.

H3b: Consumers' selection of a default private label option, positively affects their decision satisfaction.

3.3 EXPERIMENTAL DESIGN

The experimental design was provided by Mari, and it was almost analogous to the one he used in his previous research.

In order to investigate the effect of the brand in the purchase decision process of utilitarian products, it was conducted an individual-session online experiment. It was asked to each participant to purchase a utilitarian product (a pack of batteries) through Amazon Alexa, using generic search terms (broad match). Batteries represent an item often taken as an example by experts because they belong to a product category that has high potential to be disrupted by voice commerce because of its low involvement and utilitarian nature.

The trusting beliefs of each subject were manipulated, before proceeding with the fictitious purchase. The purchase task was made using a third-party skill called "Voice Commerce", which was developed by the researcher Mari following systematic machine behavior observations. This skill was created to mimic the original purchase process on Alexa in terms of flow, structure, and tone of the

interaction to give the user the perception to speak directly with Alexa during the whole task. As already mentioned in the previous chapter (Paragraph 2.6), an ordinary Alexa user usually is not able to differentiate Alexa's standard capabilities from third-party apps, so a proprietary app that replicates Alexa's shopping functionalities constitutes an opportunity to examine the default effects in a controlled but realistic purchase environment. Then, thirty-five "AA" battery brands were coded into the application. Trying to control the effect of quality and quantity, it was decided to recommend batteries with the same product information and quantity. The main difference with respect to the previous experiment conducted by Mari stands in the decision of designing the Alexa skill such that in each session, the first recommended option (i.e., default option) was fixed to Amazon Basics. On the other hand, in the previous research, the order of the thirty-five brands was completely randomized. Thus, the brand appearing as default option was always different and randomly chosen.

In the current experimental design, in each session, Alexa suggested as the first option the Amazon's private label "Amazon Basics". Then, the order of the recommended brands from the second option forward was randomized. Therefore, except Amazon Basics, which was constantly the first option, the other brands had the same chance to show up to the user regardless of their popularity or market share. Moreover, in each session Amazon Basics price was the lowest value possibly found in the study (2.99 euros). Whereas, the price of the other brands was

randomly associated with one of five price points representing the range between private label (the cheapest), and well-known brands (the highest) prices in the Italian online shops and retailers (EU 2.99, 3.49, 3.99, 4.49, 4.99). Across all the recommended options by Alexa, brand name and price were supposed to be the only variable elements.

3.3.1 Participants

A total of 63 students were recruited online from the Università Politecnica Delle Marche through an email informing about the study, which was sent only to those students above the age of 18 and fluent in English. Because of the COVID-19 pandemic, the authors recruited students online and conducted the experiment remotely. The online experiment required the students firstly to interact with a researcher, and then with a voice assistant. Therefore, it was asked them to be alone in a calm and undisturbed environment with a computer (no mobile devices) and to make sure to have a stable Internet connection with a working camera and microphone. Researchers assigned a number to all approved subjects. Using software for block randomization (graphpad.com), participants were randomly assigned to one of two study conditions (1=high trust, and 2=low trust). A total of 60 subjects (30 per condition) were included in the analysis, as they: i) showed-up to the Zoom call on time, ii) passed the attention check at the beginning of the study,

iii) made a purchase using Alexa without being supported by the researcher. To all participants were offered the pack of batteries they bought. Since the university remained closed due to the COVID-19 pandemic, students were notified to pick up the purchase when it opens again.

3.3.2 Manipulation

It was created a fictitious Consumption Reports (CR) from a non-profit organization (see in the Appendix A – Instructions) aiming at manipulating participants' trusting beliefs towards Amazon Alexa. Two versions of the report were available, one containing excellent and one poor VAs capabilities of VAs during shopping. The only difference between the two reports is provided by the positive or negative connotation of the sentences. One of the two versions was assigned to each participant, depending on the condition previously allocated to them (high vs low trust). Subjects were required to read and reflect on a consumer report, which was developed around nine sentences, ordered in bullet points. An attention check was also included at the end of the report with the manipulated participants being required to count the number of the statements (bullet points) presented supporting the excellent or poor ratings of VAs like Alexa.

3.3.3 Design and task procedure

During the experiment was used a 3rd generation Amazon Echo Dot device.

One participant at a time joined the virtual meeting room on Zoom, where it was the researcher waiting for him, who as first thing checked whether all technical requirements were respected, and ensured that the subjects were alone and undisturbed in the room. Then, the researcher introduced the study, by saying: i) "*This is Alexa, a voice assistant used for a variety of tasks like checking the weather forecast, or listening to music. For example, (holding the device) I can say "Alexa, what's the weather forecast in Ancona?""* (Alexa's response represents a demo of a common feature of the device); ii) *"With Alexa, you can also purchase household and grocery items, like shampoo or batteries. The scope of this experiment is to purchase product for real, as explained in the instructions I will share with you".* iii) *"This study will last around 20 minutes. In case any instruction is unclear, or you need technical help, please use the chat on Zoom to reach me out. In that case, I will be back to you as soon as I receive a notification on my phone".*

Then, the researcher shared a link on the chat on Zoom with all the instructions needed to complete the experiment, including how to buy the batteries using Alexa, and a questionnaire (see Appendix B – Questionnaire) to fill out afterward. Later, the researcher left the room leaving the participant alone with Alexa.

The task required participants to purchase one pack of four AA batteries on Alexa. They started the process by saying "Alexa, open Voice Commerce", provided a

code, and asked for batteries. In the study instructions, it was written to say "yes" when ready to place an order and "no" if they wanted to hear more options. Alexa recommended one brand at a time (see Appendix A – Instructions – How to use Alexa). Therefore, participants could decide whether to choose directly the default option, saying yes to the first suggestion, or continue to listen to other alternatives (default option=1; other brands=0).

Once the subjects finished the task and the survey, the researcher came back to the Zoom video call, where informed the subject about the fictitious nature of the customer report, and the non-commercial purpose of the "Voice commerce" application that is not available on market right now.

The research intent was to explore the relationship of the users with Alexa, not with Amazon, for this reason, the retailer's name was not mentioned during the experiment not to divert the attention from the personal assistant.

3.3.4 Measures

On the survey that all participants were required to fill out, study participants expressed their level of agreement with a total of 77 statements that were designed on a 7-point Likert scale (1=strongly disagree; 7=strongly agree), allowing participants to express how much they agree or disagree with a particular one. The independent variable, consumers' trusting beliefs, was constructed based on the

questions/statements representing competence, benevolence, and integrity of VAs. Whereas, the dependent variable, decision satisfaction, was constructed based on the questions/statements concerning not only every participant's final selected product, but also his/her evaluation of the entire purchasing process (see Appendix C – Main variables' measures).

In addition, were collected for exploratory purposed secondary variables such as choice confidence, intention to adopt as a delegate agent/ decision aid, post-purchase satisfaction decision, (future) intention to follow voice assistant advice.

Moreover, the questionnaire was used to collect data about all the participants' basic demographic information including age, gender, nationality, their personal characteristics regarding satisficing, optimizing, maximization, propensity to technology, prior knowledge about batteries and trust propensity, as well as their past-experience with VAs and voice shopping. Then, we explored the shopper's choice with regard to price and reason for default choice.

In addition, during the experiment extra measures were gathered from the log data of the Alexa skill. Specifically, we stored the consideration set size, namely the number of options considered by the user before making the purchase decision, consideration set brand, namely the number of brands known before the experiment out of the total brands recommended by Alexa, consideration set price, namely the average price recommended by Alexa, and decision time.

3.4 RESULTS

On a total of 60 participants, aged from 20 to 34 (*M*age=26), 80% were Italians, whereas the remaining part came from 10 different countries, such as Turkey, USA, Vietnam, Ghana, Cameroon, Brazil, China, Pakistan, Romania, and Nigeria. Groups were almost evenly distributed in terms of gender, with 60% of women. About 50% of all the participants claimed they have never used any physical VAs, while 25% generally use VAs once a month or more often. Moreover, 80% of the participants have never bought a product using VAs, only 16.7% of the total claimed "rarely" or "occasionally" and 3.3% once a month or more. Finally, 92% of the subjects never bought batteries using voice assistant, and the remaining part claimed they did "rarely".

One-way ANOVA tests of differences in means across high and low groups (coded: 1=high trusting beliefs; 2=low trusting beliefs) is presented to exclude that the two conditions behave significantly different from each other. We look at factors including age, gender, nationality, frequency of using VA, frequency of buying products using VA, frequency of buying batteries using VA, and study duration in second. Respondents belonging to the two conditions show no statistical mean difference for all control variables with the exception of study duration in seconds (p=0.008), and frequency of voice commerce usage (p=0.040). To address this problem, these two variables were included in the analysis to verify that they did not influence the study result.

3.4.1 Manipulation Check

An ANOVA test was used to check whether the trust manipulation worked well, the test was conducted to compare the trusting beliefs scores in the high trust group (mean=4.77, sd=0.83), and the low trust group (mean=4.26, sd=1.02). At the 95% of confidence level, the two groups are statistically different from each other, in relation to their trusting beliefs toward Alexa, $F_{1, 58}$= 4.467, p=.039. Therefore, it is demonstrated that the trust manipulation successfully changed the users' trust perception in Alexa.

Descriptives

Trusting beliefs Alexa

	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
					Lower Bound	Upper Bound		
1	30	4.7667	.82970	.15148	4.4568	5.0765	3.25	6.67
2	30	4.2583	1.02328	.18682	3.8762	4.6404	2.50	6.25
Total	60	4.5125	.95851	.12374	4.2649	4.7601	2.50	6.67

ANOVA

Trusting beliefs Alexa

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	3.876	1	3.876	4.467	.039
Within Groups	50.330	58	.868		
Total	54.206	59			

Table 3.1: ANOVA test in terms of Trusting Beliefs toward Alexa (1=high trust, and 2=low trust)

Moreover, were measured not only the trusting beliefs toward Alexa, but also those toward Amazon to ensure that the manipulation affected only the trusting beliefs toward Alexa, and not toward Amazon. This represent an original contribution of this study. Indeed, this differentiation considers that Amazon and Alexa are two

distinct entities, and the research intent was to explore the relationship of the users with Alexa, not with Amazon. That's the reason why the retailer's name was only mentioned during the selection process (Amazon Basics) and not during the experiment.

An ANOVA test was conducted to check whether the trust manipulation towards Alexa affected trusting beliefs in Amazon. The author compared the scores of trusting beliefs towards Amazon between the high trust (mean=4.73, sd=0.99), and low trust groups (mean=4.65, sd=0.83). Here, it is possible to notice that the two mean are closer. At the 95% confidence level, the two groups are not statistically different from each other, in relation to their trusting beliefs toward Amazon $F_{1, 58}$ = 0.134, p=0.716. That proves that the manipulation affected the perception of trust for Alexa, and not for Amazon.

Descriptives

Trusting belief Amazon

	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
					Lower Bound	Upper Bound		
1	30	4.7333	.99216	.18114	4.3629	5.1038	2.67	6.83
2	30	4.6472	.82516	.15065	4.3391	4.9553	3.08	6.17
Total	60	4.6903	.90576	.11693	4.4563	4.9243	2.67	6.83

ANOVA

Trusting belief Amazon

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	.111	1	.111	.134	.716
Within Groups	48.293	58	.833		
Total	48.404	59			

Table 3.2: ANOVA test in terms of Trusting Beliefs toward Amazon (1=high trust, and 2=low trust)

3.4.2 Default effect

The results confirmed that the consumers' tendency to choose the default option persists even in scenarios where the first suggestion is a private label associated with the voice assistant's manufacturer. In particular, the tendency was even more pronounced than in the previous study, in which 60% of participants have purchased the first recommended brand. Here, 72%, of the subjects selected a default option, and the 93% of the participants relied on the first three alternatives provided by Alexa to finalize the purchase.

It seems that the suggestion of Amazon Basics' as default choice amplifies even more the tendency to choose a default option. This result involve critical managerial implications for the owners of brands others than private labels, because they could seriously weaken their position if Alexa will always present its private label as default in the reality. Brands should carefully consider this warning sign. The author will discuss further about the implication in Paragraph 3.5.

Moreover, in support to this statement, during the experiment three subjects listened to more alternatives (i.e., do not accept immediately the first option), but then they have restarted the process to select Amazon Basics[11]. In particular, 77% of the

[11] The developed skill "Voice commerce" don't give the possibility to choose the previous option once discarded. For example, once the subject arrive to the third option, he cannot say: "Alexa, I want to buy the first option". The only possible way to buy the first option is to reinitiate the process and buy immediately the first option when presented. This was what happened with the aforementioned three participants. However, this mode was not explained in the instruction, the three subject have guessed how to buy the first option, even if already discarded, by their selves.

subjects purchased Amazon Basics.

These three participants were not considered among those who selected the default option.

Default choice

			Percent		Cumulative Percent
Valid	0	17	28.3	28.3	28.3
	Default option	43	71.7	71.7	100.0
	Total	60	100.0	100.0	

Table 3.3: Frequency table showing the percentage of participants who choose a default option (no default choice=0; default choice=1)

3.4.3 Trust effect on default choice

A Chi-Square test between trust condition (high trusting beliefs=1; low trusting beliefs=2) and default choice (no default choice=0; default choice=1) was conducted to see whether there is an association between these two categorical variables, so to understand whether the two variables are independent or related. From the Crosstabulation (Table 3.4), it is possible to see how much people belonging to the first condition (high trust) chose to purchase the default option (20), and how much people belonging to the second condition (low trust) decided to buy the default choice (23).

The key result in the Chi-Square Tests table is the Pearson Chi-Square. From the table below (Table 3.4), it is possible to notice that the value of the test statistic is

0.739. Moreover, since the test statistic is based on a 2x2 Crosstabulation table, the degrees of freedom (df) for the test statistic is 1. The corresponding p-value of the test statistic is p = 0.390.

Since the p-value is greater than our chosen significance level ($\alpha = 0.05$), there is not enough evidence to suggest an association between trusting beliefs and default choice ($\chi2(1) >= 0.739$, $p = 0.390$).

Condition * Default choice Crosstabulation

Count

		Default choice 0	Default choice 1	Total
Condition	1	10	20	30
	2	7	23	30
Total		17	43	60

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	.739[a]	1	.390

Table 3.4: Chi-Square between condition (high trust=1; low trust=2) and default choice (no default choice=0; default choice=1)

Although we assumed that high trusting beliefs toward voice assistant positively affect the tendency of consumers to opt for the default choice, those is in the low trust condition decided to buy the default option more than those in the high trust

condition (23 vs 20). However, the negligible difference between the two groups resulted in a p-value is greater than our chosen significance level ($\alpha = 0.05$).

A small sample, which of course represent the major limitation to this study, did not allowed the author to run a robust statistical validation of this hypothesis. In other words, the low number of subject that selected a brand other than Amazon Basics (i.e., the default option) doesn't allow to observe a strong difference between the two groups (high and low trust) in respect to their shopping decision (default choice or not). In any case, a strong tendency to choose the default can be observed. In sum, H2 is not supported.

3.4.4 Trust effect on decision satisfaction

A linear regression was conducted to examine the trust-satisfaction effect. The final goal was to understand whether trusting beliefs toward voice assistants have a direct and positive effect on decision satisfaction. Indeed, the assumption was that higher is the trust, greater is the decision satisfaction. It was done through SPSS Statistics that generated three main tables required to analyze the results. In this study, Trusting Beliefs represent the independent variable (X), whereas Decision Satisfaction is the dependent variable (Y). It was considered the whole sample (n=60) without making a distinction between the two condition, high trust and low trust.

The first table is the Model Summary (Table 3.5) which provides the R and R^2 values.

The R value is equal to 0.453, and indicates a good degree of correlation. The R^2 value (R Square) is equal to 0.205 indicates how much of the total variation in the dependent variable, Decision Satisfaction, can be explained by the independent variable, Trusting beliefs. In this case, 20% of the total variation in Decision Satisfaction can be explained by the trusting beliefs. The result is good, and the fact the percentage is not very high could depend on the small sample.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.453[a]	.205	.191	.90462	.205	14.945	1	58	.000

a. Predictors: (Constant), Trusting beliefs Alexa

Table 3.5: Linear regression: Trusting Beliefs (X) on Decision Satisfaction (Y): Model Summary

Then, the second table generated is the ANOVA, which is needed to understand how well the regression equation predicts the Decision Satisfaction (Y). The table indicates that the regression model predicts the dependent variable significantly well, since the significance (Sig.=0.000) of the regression model is lower than 0.05. It indicates that, overall, the regression model statistically predicts the dependent variable, in this case Decision Satisfaction (i.e., it is a good fit for the data).

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	12.230	1	12.230	14.945	.000[b]
	Residual	47.464	58	.818		
	Total	59.694	59			

a. Dependent Variable: Decision satisfaction total

b. Predictors: (Constant), Trusting beliefs Alexa

Table 3.6: Linear regression: Trusting Beliefs (X) on Decision Satisfaction (Y): ANOVA Table

Finally, the table Coefficients provides the coefficient of trusting beliefs (β= 0.475) on decision satisfaction, with a t-value=3.866, which is significant (p=0.000). The coefficient is positive, therefore, it is possible to confirm that consumers' trusting beliefs positively affect the satisfaction. The positive relationship between consumers' trusting beliefs and their decision satisfaction is good and significant. On average and ceteris paribus, one unit increase in a participant's trusting scores towards Alexa is associated with about 47.5% increase in their overall purchasing decision satisfaction.

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Correlations			Collinearity Statistics	
		B	Std. Error	Beta			Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	2.804	.567		4.948	.000					
	Trusting beliefs Alexa	.475	.123	.453	3.866	.000	.453	.453	.453	1.000	1.000

a. Dependent Variable: Decision satisfaction total

Table 3.7: Linear regression: Trusting Beliefs (X) on Decision Satisfaction (Y): Coefficients

Then, it was conducted a multiple regression analysis analogous to the one presented above, with “Trusting Beliefs”, “Study duration in seconds”, and “Frequency of voice commerce usage” as independent variables, and “Decision Satisfaction” dependent variable. The control variables that resulted different among the two condition (high and low trust), namely “Study duration in seconds” and “Frequency of voice commerce usage”, were added to the analysis to avoid possible omitted variable biases and improve the accuracy of the model. The regression in Table 3.8 shows that after controlling the variables, trusting beliefs still positively affect people’s satisfaction, though the significance has dropped in magnitude, the estimate (p-value=0.02) remained statistically significant.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics			
					R Square Change	F Change	df1	df2	Sig. F Change
1	.487[a]	.237	.197	.90158	.237	5.813	3	56	.002

a. Predictors: (Constant), FQ. VC usage, Duration study (in seconds), Trusting beliefs Alexa

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	14.175	3	4.725	5.813	.002[b]
	Residual	45.519	56	.813		
	Total	59.694	59			

a. Dependent Variable: Decision satisfaction total

b. Predictors: (Constant), FQ. VC usage, Duration study (in seconds), Trusting beliefs Alexa

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	2.996	.636		4.713	.000
	Trusting beliefs Alexa	.480	.130	.458	3.704	.000
	Duration study (in seconds)	.000	.000	-.124	-1.025	.310
	FQ. VC usage	.159	.147	.130	1.087	.282

a. Dependent Variable: Decision satisfaction total

Table 3.8: Multiple regression analysis

Therefore, it is possible to conclude that trusting beliefs toward voice assistants have a direct and positive effect on decision satisfaction. People having more trust towards VAs tend to be more satisfied with their purchased products recommended to them. Thus, H3a is supported.

3.4.5 Default option effect on consumers' decision satisfaction

It was analyzed whether the decision satisfaction was affected by the default option, when the latter coincides with the VAs private label.

It was conducted a hierarchical regression analysis, where the independent variable are Trusting Beliefs and Default Option (Default option; No default option), and dependent variable is Decision Satisfaction.

The main goal was to understand the relative contribution of Default Option in explaining the variation in Decision Satisfaction. It was considered the whole sample (n=60) without making the distinction between the two conditions, low and high. As it can be seen in Table 3.9, the R value (Multiple correlation coefficient) is equal to 0.300, and can be considered one measure of the quality of the prediction of the dependent variable. Here, the value is not so high probably due to the small sample; however, it indicates a good level of prediction. Moreover, "R Square" value is equal to 0.090, which is relatively low but statistically significant. It means that 9% of variance in Decision Satisfaction (dependent variable) can be explained by the selection of the Default Option.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.300[a]	.090	.075	.96762
2	.557[b]	.311	.286	.84973

a. Predictors: (Constant), Default choice

b. Predictors: (Constant), Default choice, Trusting beliefs Alexa

Table 3.9: Hierarchical regression analysis: Model Summary

The F-ratio in the ANOVA (Table 3.10) tests whether the overall regression model is a good fit for the data. The table show that the independent variable, Default Option, statistically significantly predict the dependent variable, Decision Satisfaction, $F(1, 58) = 5.756$, $p < 0.05$. Therefore, the regression model is a good fit of the data).

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	5.389	1	5.389	5.756	.020[b]
	Residual	54.305	58	.936		
	Total	59.694	59			
2	Regression	18.538	2	9.269	12.837	.000[c]
	Residual	41.156	57	.722		
	Total	59.694	59			

a. Dependent Variable: Decision satisfaction total

b. Predictors: (Constant), Default choice

c. Predictors: (Constant), Default choice, Trusting beliefs Alexa

Table 3.10: Hierarchical regression analysis: ANOVA Table

From table 3.11, it is possible to see the coefficient β= 0.721 which is statistically significant (p-value=0.005), even when added to the main independent variable Trusting Beliefs. The coefficient (β= 0.721) indicates how much Decision Satisfaction varies with Default Choice, when all other independent variables are held constant. Therefore, it indicates that when people choose the default option Amazon Basics, the decision satisfaction increase of 0.721 units, on average ceteris paribus.

Then, it is possible to notice from Table 3.11, that Default Choice is a statistical significant independent variable since the p-value (Sig.=0.005) is lower than 0.05, the confidence level (t=2.956; p-value=0.005).

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	4.471	.235		19.049	.000
	Default choice	.665	.277	.300	2.399	.020
2	(Constant)	2.205	.569		3.872	.000
	Default choice	.721	.244	.326	2.956	.005
	Trusting beliefs Alexa	.493	.116	.470	4.267	.000

a. Dependent Variable: Decision satisfaction total

Table 3.11: Hierarchical regression analysis: Coefficients

To sum up, Default Choice statistically significantly predict Decision Satisfaction, F (1, 58) = 5.756, p< .005, R^2=0.090. Therefore, the increase in decision satisfaction is not given only by the consumers' trusting beliefs. The fact participants bought the default option, Amazon Basics, contributes to predict decision satisfaction. There is a brand effect: on average and ceteris paribus, the more people purchased Amazon Basics, the more they were satisfied. Therefore, Default option is a relevant variable.

3.5 CONCLUSIONS AND MANAGERIAL IMPLICATIONS

The research aims to widen the existing study conducted by Mari "The role of trusting beliefs in voice assistants during voice commerce", focusing on the effect of the default option when it consists of the voice assistant private label. The study explores the effect of brand in the online purchase decision process, considering a utilitarian product searched asking for generic product categories terms (i.e. batteries). In this case, Alexa performs a so-called "broad match" that differentiates from the "exact match" that happens when consumers ask for a specific brand (e.g. Duracell Batteries).

It was analyzed the impact of a default choice when it consists of the VA's private labels to have insights regarding their effects on brands, considering that Alexa is

connected to Amazon, which operating as a retailer can manage, as it desires, the online product placement on voice commerce.

In the previous research, Mari (2020) has demonstrated that customers' trusting beliefs in a VA (in terms of competence, benevolence, and integrity) positively and directly affect they decision satisfaction. The consideration set size (n. of options considered before the purchase) mediates the relationship between trusting beliefs and decision satisfaction, the greater the consideration set size and the lower is the decision satisfaction. Besides, he suggested that consumers' trusting beliefs positively affect the consumers' tendency to select a default option.

In this study, the author firstly verified whether this "default effect" remained dominant when the first recommended brand is the VA private label, in this case, Amazon Basics.

Furthermore, the author analyzed whether trusting beliefs in voice assistants explain the consumers' tendency to select a default choice. In the current study, the two groups, high and low trust, both strongly relied on the default option; therefore, there is not a statistical difference between them. A small sample, which of course represent the major limitation to this study, did not allowed the author to run a robust statistical validation of this hypothesis.

Finally, the results indicate that consumers' trusting beliefs in voice assistants have a direct and positive effect on their decision satisfaction. This emphasizes the sever impact voice commerce could have on brands. Indeed, independently from the

purchased brand, if consumers trust the voice assistants they will be more satisfied. Therefore, consumers give less importance to the brand, when they buy utilitarian products through voice commerce. As a consequence, this could disadvantage other brands, like Duracell or Varta, in the case of batteries. One of the original functioning of branding is that it provides consumers a reliable way to determine the quality of goods while providing manufactures means to gain customers trust (Labecki et al., 2018). However, it seems that brands might lose their importance in the context of voice commerce, since they do not fill anymore their initial function of signaling the product's quality. It confirms that VAs are behaving as a sort of intermediary between brands and consumers (Mari et al., 2020).

Furthermore, the research shows that those who bought the default private label option, Amazon Basics, were more satisfied than the others. This might suggest that who decided to go on listening more alternatives, most of the time figured out that the other brands were unknown and had a higher price; therefore, they ended up more unsatisfied with respect to those who accepted the first recommendation. This result goes to highlight how much private labels might affect brands, in the context of voice commerce.

Two main facts has to be considered: firstly, the research demonstrated that consumers tend to choose a default option, and when they do it, they are more satisfied; secondly, Alexa can decide to place its private label (Amazon Basics) as the top consumer choice. These two facts combined open up several implications

for brands other than private labels.

Indeed, each time the voice assistants process a “broad match” request, Alexa could decide to suggest its private label items, if available (as intentionally designed in this experiment). Besides, on voice commerce there is a limited “shelf space”, because items are recommended one at a time. In addition, it is demonstrated that consumers tend to listen to three options, on average, before completing the purchase. Consequently, brands could weaken and worsen their market position.

To address this problem, managers should consider investing in voice commerce within a short time period (Bonvin, 2020).

Firstly, managers should invest in building the company presence on the platform, as soon as possible, not to be knocked down by competitors and private labels. Indeed, if your companies didn’t create a voice commerce application and your competitors have already developed it, Alexa will firstly suggest their products. Whereas if no one in the product category have their app Amazon will recommend its private label as the first option, if available. For example, assume that Pizza Hut has developed a skill for Amazon Echo, whereas Domino’s Pizza still doesn’t have it. If consumers start to order pizza on the device, as the first thing, Alexa will suggest to them Pizza Hut, because it provides the app. Therefore, customers start to build their purchase habits over this app. Eventually, if Domino’s Pizza will decide to create its own skill could risk being too late, because users will be already “lock-in” this process, and automatically buy from Pizza Hut. The VA sees the

purchase from Pizza Hut, as an implicit customer's preference, so it will be hard for Domino's Pizza to break this mechanism (Smith, 2020). Building their presence on the platform represents a good way for brands to limit the negative effect caused by VAs' choice architecture and private labels.

Moreover, managers should find a balanced trade-off between investing in traditional marketing and voice-marketing activities, both are needed to enhance the voice commerce potentialities. Previous research (Bonvin, 2020) suggested that managers should not fear to dedicate more than one-third of their yearly marketing budget to voice marketing activities (Bonvin, 2020). Since the power of VAs on consumers is increasing with its growing diffusion, companies need to find new ways to gain or keep a good market position. For example, to exploit the voice commerce experience companies should start to optimize their voice search engine, especially considering the limited space reserved for the top search result. Brands need to work on defining their voice strategy to increase the probabilities of being picked up among the first suggestions (10vorne, 2020). Besides, they should pay attention to how information about the products are presented, in particular the tone of voice and the words used to deliver the message, play a critical role in voice commerce because they could persuade people to buy. It is demonstrated that the personalization of the message affect positively the customer attitude (Rhee & Choi, 2020).

Along with the voice marketing activities, marketers should reinforce their brand

building across all the other already established traditional and digital channels, to raise brand awareness and recall. This will be critical because if companies are capable of creating a strong attachment with customers, it is more likely that people will ask for their specific brand, and in this case, Alexa will perform an "exact match" providing the brand requested, if available. Therefore, consumers will less influenced by machine behavior (Mari et al., 2020).

3.6 LIMITATIONS AND FUTURE RESEARCHES

The study design is subject to several limitations, some of which offer interesting avenues for developing further researches.

Firstly, it is critical to keep in mind that the results obtained from this research are valid only for utilitarian products using broad match; as a consequence, future researches could investigate more regarding what happens when consumers purchase high involvement products and with different search modes (e.g. exact match).

Secondly, due to the Coronavirus pandemic situation, the lab experiment had to be transferred into the online session, making it hard to perfectly control for all the exogenous conditions, which would compromise the overall satisfaction of participants within the whole interaction process.

In addition, future researches could investigate further whether the decision satisfaction comes from having bought a default option or from having bought the private label, like Amazon Basics. Indeed, in the current study, the default option coincides with Amazon Basics, and it was not possible to differentiate clearly, if the effect is derived from the default or the brand.

Finally, the major limitation is that the experiment sample was particular small (n=60), and mainly consisted of students from an Italian university, "Università Politecnica Delle Marche", therefore it may not be as representative as possible, considering how much diverse are the real VA users.

CONCLUSIONS

Over the years, marketing has been always influenced by technology. Today, marketing can leverage Artificial Intelligence (AI) systems to gather, analyze and store customers' data aiming at improving the customer journey.

Recently, AI technologies have led to the rising of a new trend that has the potential to greatly affect digital marketing in the future: consumers are increasingly buying and using smart speakers. Thanks to the artificial intelligence embedded in them, VAs can perform a wide array of activities. Although people mainly used them to carry out basic tasks like listening to music or asking the weather forecast, lately users are starting to increasingly place orders through VAs. Therefore, VAs fulfill a novel function from a commercial perspective: they are becoming a new consumer touchpoint for brands allowing for different forms of interaction (Smith, 2020).

The series of activities carried out to complete an order through a voice assistant goes under the label of "voice commerce". Nowadays, VA's are functioning as a salesperson in the context of voice commerce, thus they have the potential to redefine the relationship among consumers, brands, and retailers. Despite the great opportunity provided by voice commerce for brands and consumers, studies addressing the disruptive impact of VAs on the marketing practice are very rare (Bonvin, 2020).

The present work investigated the role of AI technologies in marketing, by highlighting how they can be used in the context of voice commerce through the application of VAs. Since voice commerce has the potential to affect consumers' purchase journey, companies need to understand how to approach and further exploit this new channel.

The experiment conducted with 60 students from the Università Politecnica Delle Marche allowed the author to draw some important implications about the role of voice commerce both for academics and practitioners. The experiment simulated a purchase of a utilitarian product (a pack of batteries) with broad search terms by using Amazon Alexa who was set to suggest as the first option the Amazon's private label "Amazon Basics", with one of the lowest price possible found.

Firstly, the research showed that people's tendency to select a default option remains dominant when it coincides with the VA's private label. Precisely 72% of the subjects relied on the first item suggested, Amazon Basics. This inclination is known as "default effect" or "status quo bias", and confirms that humans tend to favor the status quo over other equally valuable alternatives. Considering that VAs can decide to put always their private label as the default choice, this element could have great implications for industrial firms and brands.

Secondly, the study indicates that consumers' trusting beliefs in voice assistants have a direct and positive effect on their decision satisfaction. This emphasizes the severe impact voice commerce could have on brands: independently from the

purchased brand, if consumers trust the voice assistants, they will be more satisfied. Therefore, it seems that consumers give less importance to the brand value.

Among the other things, the research shows that those who bought the default private label option, Amazon Basics, were more satisfied than the others.

These results highlight how much private labels might weaken the national brands market position, in the context of voice commerce. Consequently, managers and brands should invest in voice commerce within a short time period (Bonvin, 2020) thus building their presence on them and developing their skills for these new platforms. Therefore, they will be able to limit the negative effects caused by VAs' choice architecture and private labels. Indeed, if a competitor develops a voice commerce application before others, Alexa will firstly suggest its products. Whereas if no one in the product category have their app, Amazon will recommend its private-label as the first option.

Finally, managers should find a balanced trade-off between investing in traditional marketing and voice-marketing activities since both are needed to enhance the voice commerce potentialities. On one hand, companies should start to optimize their voice search engine to increase the probability of being picked up among the first recommendation. On the other hand, marketers should reinforce their brand building across all the other already established traditional and digital channels, to raise brand awareness and recall.

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APPENDIX A – INSTRUCTIONS

Report instruction - High trust condition

Please take your time to read and reflect on the analysis by "Consumption Reports" you find on the next page.

When the report appears clear to you, please answer the question at the end of the page.

Consumption Reports (CR) is a nonprofit organization dedicated to unbiased product testing and consumer-oriented research. CR uses its independent and rigorous research to inform people's purchase decisions. CR has tested the shopping capability of voice assistants like Alexa. A summary of the findings is available below.

After extensive testing, our team of experts concluded that voice assistants like Alexa deliver excellent results when used for shopping.

When asking a voice assistant to buy a product, the following correct practices were reported:

- Voice assistants are experts in assessing products.
- Voice assistants have good knowledge of products.
- Voice assistants are competent and effective in providing recommendations.

- Voice assistants put the customer's interest first.
- Voice assistants want to understand customer's needs and preferences.
- Voice assistants are interested in customer's well-being, not just their own.
- Voice assistants guide the user with their product recommendations.
- Voice assistants are honest in their product recommendations.
- Voice assistants provide unbiased product recommendations.

Given the fair practices expressed above, CR considers voice assistants like Alexa able to provide a trustworthy shopping service. Thus, CR marks voice assistants like Alexa as reliable and honest for shopping activities.

Source: consumptionreports.org – May 2020

Attention check

Please count how many bullet points (statements) in the report above support the positive rating of voice assistants like Alexa.

The number of bullet point statements that support the positive rating of voice assistant like Alexa is:

Report instruction - Low trust condition

Please take your time to read and reflect on the analysis by "Consumption Reports" you find on the next page.

When the report appears clear to you, please answer the question at the end of the page.

Consumption Reports (CR) is a nonprofit organization dedicated to unbiased product testing and consumer-oriented research. CR uses its independent and rigorous research to inform people's purchase decisions. CR has tested the shopping capability of voice assistants like Alexa. A summary of the findings is available below.

After extensive testing, our team of experts concluded that voice assistants like Alexa deliver poor results when used for shopping.

When asking a voice assistant to buy a product, the following incorrect practices were reported:

- Voice assistants are not experts in assessing products.
- Voice assistants do not have good knowledge of products.
- Voice assistants are not competent and effective in providing recommendations.
- Voice assistants do not put the customer's interest first.

- Voice assistants do not want to understand customer's needs and preferences.
- Voice assistants are not interested in the customer's well-being, just their own.
- Voice assistants misguide the user with their product recommendations.
- Voice assistants are not honest in their product recommendations.
- Voice assistants provide biased product recommendations.

Given the unfair practices expressed above, CR considers voice assistants like Alexa unable to provide a trustworthy shopping service. Thus, CR marks voice assistants like Alexa as unreliable and dishonest for shopping activities.

Source: consumptionreports.org – May 2020

Attention check

Please count how many bullet points (statements) in the report above support the negative rating of voice assistants like Alexa.

The number of bullet point statements that support the positive rating of voice assistant like Alexa is:

Task instruction - High trust condition

Your task

"Voice commerce" is a shopping application provided by the voice assistant "Alexa". You can buy a large assortment of household items, fresh produce, electronic gadgets, beauty products, and so on.

Your task is to buy on Alexa one pack of AA batteries (pack of 4 items) among different choices. These batteries can be used for electronic devices like a TV remote control, clock, or wireless mouse.

After your order is confirmed, your batteries are shipped to the researcher's office and can be collected at UNIVPM.

How to use Alexa

Going back to your Zoom's window (video call), you find on the desk the voice assistant "Alexa". This device responds to your voice commands.

- To initiate its shopping capability, say, "Alexa, open Voice Commerce";
- You are then asked to enter the code **"buy batteries"**;
- You are now ready to shop for AA batteries (it reads "double-A batteries");
- Say "yes" when you are ready to purchase the specific option. Say "no" if you want to hear more options.

IMPORTANT: *Please don't close this window, you need to return to this survey and click the arrow (next) as soon as your order is confirmed.*

Back from task

Now that your order is successfully placed, please answer the questions in the following pages.

IMPORTANT: *If your purchasing task was not completed for any reason, please ask for assistance using the chat available on ZOOM. A researcher will contact you shortly.*

Task instruction - Low trust condition

Your task

"Voice commerce" is a shopping application provided by the voice assistant "Alexa". You can buy a large assortment of household items, fresh produce, electronic gadgets, beauty products, and so on.

Your task is to buy on Alexa one pack of AA batteries (pack of 4 items) among different choices. These batteries can be used for electronic devices like a TV remote control, clock, or wireless mouse.

After your order is confirmed, your batteries are shipped to the researcher's office and can be collected at UNIVPM.

How to use Alexa

Going back to your Zoom's window (video call), you find on the desk the voice assistant "Alexa". This device responds to your voice commands.

- To initiate its shopping capability, say, "Alexa, open Voice Commerce";
- You are then asked to enter the code **"order batteries"**;
- You are now ready to shop for AA batteries (it reads "double-A batteries");
- Say "yes" when you are ready to purchase the specific option. Say "no" if you want to hear more options.

IMPORTANT: *Please don't close this window, you need to return to this survey and click the arrow (next) as soon as your order is confirmed.*

Back from task

Now that your order is successfully placed, please answer the questions in the following pages.

IMPORTANT: *If your purchasing task was not completed for any reason, please ask for assistance using the chat available on ZOOM. A researcher will contact you shortly.*

APPENDIX B – QUESTIONNAIRE

Thinking about the purchase you have just made, please rate the degree to which you agree or disagree with each of the following statements:

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree or disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
I found the process of deciding which product to buy frustrating							
I thought the choice selection was good							
I found the process of deciding which product to buy interesting							
Several good options were available for me to choose between							
I was satisfied with my experience of deciding which product option to choose							
I would be happy to choose from the same set of product options on my next purchase occasion							

Thinking about the purchase you have just made, please rate the degree to which you agree or disagree with each of the following statements:

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree or disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
I am satisfied with the "brand" of batteries I have purchased							
I am confident that the purchased pack of batteries will be among the best I've ever had							
My choice to purchase this specific pack of batteries was a wise one							
I am confident that the purchased pack of batteries will satisfy me							
I am satisfied with my decision to purchase this specific pack of batteries							
I am unhappy that I purchased this specific pack of batteries							
I think I did the right thing by buying this specific pack of batteries							
I feel bad regarding my decision to buy this specific pack of batteries							

Thinking about your relationship with technology, please rate the degree to which you agree or disagree with each of the following statements:

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree or disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
In general, I am interested in trying out voice assistant like Alexa							
I generally give technology the benefit of the doubt when I first use it							
I usually trust a technology until it gives me a reason not to trust it							
My typical approach is to trust new technologies until they prove to me that I shouldn't trust them							
A large majority of technologies are excellent							
I think most of technologies enable me to do what I need							

Thinking about the purchase you have just made, please rate the degree to which you agree or disagree with each of the following statements (5 statements):

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree or disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
I am willing to use this voice assistant as a tool that suggests to me a number of products from which I can choose							
I am willing to let this voice assistant to assist me in deciding which product to buy							
I am willing to let this voice assistant decide which product to buy on my behalf							
I am willing to use this voice assistant as an aid to help with my decision about which product to buy							
I am willing to delegate to this voice assistant for my decision about which product to buy							

Thinking about the purchase you have just made, which of the following options best describe your behavior concerning the "price" of batteries during voice shopping?

- I choose what I found to be a reasonable price;
- Price was not a variable I have actively considered for my choice;
- I chose the cheapest option I was presented with;
- I relied on Alexa to provide a good value for money offer.

Thinking about the voice assistant "Alexa", please rate the degree to which you agree or disagree with each of the following statements:

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree or disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
Alexa has a good knowledge about products							
Alexa puts my interest first							
Alexa is honest in its product recommendations							
Alexa provides unbiased product recommendations							
Alexa is competent and effective in providing recommendations							
Alexa wants to understand my needs and preferences							
Alexa does its best to help me							
Alexa is an expert in assessing products							
Alexa genuinely guides me with its suggestions							
I consider Alexa to be of integrity							
Alexa is interested in my well-being, not just its own							
Overall, I trust Alexa's product recommendations							

Thinking about "Amazon", please rate the degree to which you agree or disagree with each of the following statements:

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree or disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
Amazon has a good knowledge about products							
Amazon puts my interest first							
Amazon is honest in its product recommendations							
Amazon provides unbiased product recommendations							
Amazon is competent and effective in providing recommendations							
Amazon wants to understand my needs and preferences							
Amazon does its best to help me							
Amazon is an expert in assessing products							
Amazon genuinely guides me with its suggestions							
I consider Amazon to be of integrity							
Amazon is interested in my well-being, not just its own							
Overall, I trust Amazon's product recommendations							

Please rate the degree to which you agree or disagree with each of the following statements:

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree or disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
When it comes to batteries, I really don't know a lot							
I don't feel very knowledgeable about batteries							
Compared to most other people, I know less about batteries							
Among my circle of friends, I am one of the "experts" on batteries							
I have a lot of experience with batteries							

How often do you do each of the following activities?

	Never (1)	Rarely (2)	Occasionally (3)	Once a month (4)	Once a week (5)	Everyday (6)	Multiple times a day (7)
Buying batteries (Alkaline)							
Using physical voice assistants like Amazon Alexa, Google Home or Apple Pod							
Buying products (or services) using voice assistants							
Buying batteries using voice assistants							

When I have used voice assistant like Alexa or Google Home in the past, I found it to have:

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree or disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
...made easier my shopping decisions/information gathering							
...increased my time-effectiveness when gathering information/shopping							
...improved my information gathering/shopping decisions							
...enabled me to accomplish my shopping decisions/information gathering							

Please rate the degree to which you agree or disagree with each of the following statements:

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree or disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
Trusting someone or something is difficult for me							
My tendency to trust a person/thing is high							
I tend to trust a person/thing even though I have a little knowledge of it							
It is easy for me to trust a person/thing							

Thinking about your opinion about Amazon, please rate the degree to which you agree or disagree with each of the following statements:

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree or disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
Amazon is the most innovative brand in the market							
Amazon is growing in popularity							
Amazon is the most popular brand in the market							
Amazon is the leading brand in the market							

Thinking about your opinion about Alexa, please rate the degree to which you agree or disagree with each of the following statements:

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree or disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
Alexa is the most innovative brand in the market							
Alexa is the most popular brand in the market							
Alexa is the leading brand in the market							
Alexa is growing in popularity							

Please rate the degree to which you agree or disagree with each of the following statements. In the future, I will:

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree or disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
...feel confident to purchase products recommended to me by Alexa							
...feel comfortable to purchase products recommended to me by Alexa							
...feel secure to purchase products recommended to me by Alexa							

If any, which of the following brands did you know prior to this study?

- Kodak
- Toshiba
- AmazonBasics
- Panasonic
- Varta
- Maxell
- Polaroid
- Philips
- Sony
- Energizer
- Fuji Enviromax
- Duracell

(Only if you choose the first option recommended by Alexa)

I choose the first option because:

- I was not interested in receiving more options;
- I did not understand how obtain more options;
- Other (please specify)

What is your year of birth?

What is your nationality?

What is your sex?

- Male
- Female

The study is now completed. We truly appreciated your support in our research project and we wish you all the best.

APPENDIX C – MAIN VARIABLES' MEASURES

Questions considered measuring "Trusting Beliefs" (from 1=Strongly disagree; to 7=Strongly agree):

Thinking about the voice assistant "Alexa", please rate the degree to which you agree or disagree with each of the following statements:

Alexa's Competence:

1) Alexa is an expert in assessing products.
2) Alexa has good knowledge about products.
3) Alexa is competent and effective in providing recommendations.
4) Overall, I trust Alexa's product recommendations.

Alexa's Benevolence:

1) Alexa puts my interest first.
2) Alexa wants to understand my needs and preferences.
3) Alexa does its best to help me.
4) Alexa is interested in my well-being, not just its own.

Alexa's Integrity:

1) Alexa provides unbiased product recommendations.
2) I consider Alexa to be of integrity.
3) Alexa is honest in its product recommendations.
4) Alexa genuinely guides me with its suggestions.

Questions considered measuring "Decision Satisfaction" (from 1=Strongly disagree; to 7=Strongly agree):

Thinking about the purchase you have just made, please rate the degree to which you agree or disagree with each of the following statements:

1) I found the process of deciding which product to buy frustrating.
2) Several good options were available for me to choose between.
3) I thought the choice selection was good.
4) I would be happy to choose from the same set of product options on my next purchase occasion.
5) I found the process of deciding which product to buy interesting.
6) I was satisfied with my experience of deciding which product option to choose.