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**APPLICABILITY OF ARTIFICIAL  
INTELLIGENCE IN E-COMMERCE FASHION  
PLATFORMS**



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Dissertação apresentada ao IADE - Faculdade de Design, Tecnologia e Comunicação da Universidade Europeia, para cumprimento dos requisitos necessários à obtenção do grau de Mestre em Design e Publicidade realizada sob a orientação científica do Doutor Edirlei Lima, Professor Auxiliar da Universidade Europeia, e sob a coorientação científica da Doutora Clara Fernandes, Professora Auxiliar da Universidade Europeia.



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**palavras-chave**

Inteligência Artificial, Comércio Eletrônico, Plataformas Digitais de Moda, Comportamento do Consumidor

**resumo**

A inovação tecnológica e a democratização da inteligência artificial (IA) têm vindo a alavancar o potencial de sucesso em todas as áreas que conhecemos hoje, com expectativas do que ainda está para vir. A presente dissertação propõe uma análise das aplicações da IA na indústria da moda, particularmente nas plataformas de marcas de moda do comércio eletrónico, e de que forma está a ter impacto na esfera pessoal do consumidor, particularmente no processo de tomada de decisão dos consumidores da Geração Z. O âmbito da IA tem vindo a evoluir de tal forma que permitiu às empresas não só melhorar a sua oferta e a procura dos clientes, como também proporcionar uma experiência de compra que vai para além da “seleção e compra” mecânica: os pontos de contacto impulsionados pela IA influenciam e enriquecem cada fase do processo de tomada de decisão, seja de forma mais positiva ou negativa. Em última análise, esta dissertação pretende proporcionar ao leitor um melhor conhecimento sobre a IA e o comércio eletrónico de moda, bem como delinear o seu impacto no comportamento online do consumidor.



**keywords**

Artificial Intelligence, E-commerce, Digital Fashion Platforms, Consumer Behavior

**abstract**

Technological innovation and democratization of artificial intelligence (AI) have been leveraging the potential success in every field we know today, while more is yet to come. The following dissertation proposes an analysis of AI achievements within the fashion industry, particularly in e-commerce fashion brand platforms, and how it is impacting the consumer personal sphere, particularly the decision-making process of Gen-Z consumers. The field of AI has been evolving in such a way that allows companies to not only improve their supply and customer demand, but also provide a shopping experience that goes beyond the mechanical “select and buy”: AI-driven touchpoints influence and enrich each stage of the decision-making process, whether more positively or negatively. Ultimately, this dissertation intends to provide the reader a better knowledge of AI and fashion e-commerce joining applications, and to delineate its impact on the online customer journey.



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## List of Acronyms

AI	Artificial Intelligence
AR	Augmented Reality
CV	Computer Vision
DL	Deep Learning
DTC	Direct-To-Consumer
Gen-Z	Generation Z
IoT	Internet-of-Things
ITs	Information Technologies
ML	Machine Learning
NER	Named Entity Recognition
NLP	Natural Language Processing
SMEs	Small and Medium Enterprises
SCM	Supply Chain Management
VPA	Virtual Personal Assistant
VR	Virtual Reality

# **Chapter I. Introduction**

## **1.1. Research Topic**

The vast concept of artificial intelligence (AI) has been extensively used throughout the years, ever since its benefits in connecting human intelligence with computer logic have been proved. In reality, the extension across human activities and the augmentation of human tasks are what makes AI so relevant and important in so many industries, and the fashion industry is no exception (Luce, 2019).

The applications of AI in the fashion industry are very widespread, but the most far-reaching have been in trend forecasting and decision making in supply chain management, according to Chris Boos, in the Business of Fashion (2018). Yet from a customer-centric perspective such as user experience (UX) or customer service, whether being on social networks or fashion marketing, AI has an enormous potential that has been yet to be successfully invested (meaning: to reduce costs and increase efficiency): in 2017, fashion brand Everlane backed off its AI-powered chatbot on Facebook Messenger in order to concentrate their resources on the email format. Obviously, one example in an extensive industry is not very telling but it is representative of the challenges fashion brands have to face in order to better attend customers' needs and to drive profits (Boos, 2018).

Nowadays, due to the emergence of big data in a fast-paced market where the customer demand is the ruler, fashion companies need to constantly adapt their business and marketing strategies to technological innovations in order to optimize their resources and investment. A hyperconnectivity world, where people are constantly leaving digital traces and clues (data) about their needs and desires through "business transactions, physical sensors, social media networks, and other sources, continuously flow into all areas" (Thomassey & Zeng, 2018, p. 1), is leading to a major digital transformation, particularly in e-commerce approaches.

Looking over the past decade, we have been observing a major increase in online consumption and e-commerce transactions, creating a “shopping ecosystem that involves multiple devices and store concepts”, according to the *Digital Economy Compass*, a report by Statista (2020). In this context, it was rather a matter of time until brick-and-mortar retail started to invest in multi-channel strategies in order to fulfil customers’ expectations and to reinvent new ways to shop online, while simultaneously competing with giant online marketplaces such as Amazon or eBay. Mobile e-commerce, also according to Statista, has been the “fastest-growing segment” and despite being particular to certain age groups, its characteristics mostly involve artificial intelligence applications.

When observing the global e-commerce panorama, provided by Statista (2020, p. 137), fashion is expected to be the largest segment in e-commerce revenue until 2024 (the other segments include: Toys, Hobby & DIY; Electronics & Media; Food & Personal Care; and Furniture & Appliances). More generally, observing the general global AI market and its revenue forecast provided by Statista as well, it is expected to grow 41% until 2025 (2020, p. 107); from 2019, the Internet-of-Things (IoT) global market is also expected to have a growth of 40% on its revenue forecast (2020, p.121); and the Augmented Reality/Virtual Reality (AR/VR) does not stand behind with a 28% of expected revenue growth in the global forecast (2020, p. 126). These numbers are representative of the fact that technological innovations will hardly slow down within the next five, or even ten years, alongside e-commerce investment and optimization.

Although these forecasts predict a very positive future, it would be imprudent not to mention the current COVID-19 pandemic which has been forcing worldwide companies to adapt, restructure their business models and reinforcing the omnipresence of the digital environment, while dealing with a more-than-ever unstable consumer behavior. Due to the pandemic, the consumer online interest in fashion and apparel decreased 27% (Statista, 2020, p. 66). However, despite these troubled times, fashion companies can seek this window of opportunity to work more effectively in their multi-channel strategies (shopping apps or AR, to mention a few), to excel their customer relationship or even invest in new segments, such as mobile e-commerce. Here, the role of AI can reach its maximum potential

and it is for that reason research across its applicability can deliver a stimulating and constructive investigation.

Therefore, this dissertation intends to consider e-commerce AI-based approaches and to provide an analysis on how fashion e-commerce has been, in fact, following these technological innovations, with a particular focus on the user experience and customer service-related technology. As mentioned before, there are other technological applications of artificial intelligence in the fashion industry: besides fashion forecasting and supply chain intervention, which can be differentiated in several stages such as product design, fabric/apparel production and distribution (Giri et al., 2019), other applications regarding more industry-wide business areas like intelligent tracking systems and other data-based processes (inventory control is one example), can also be found. However, through a communication and marketing perspective, it is far more interesting to center this investigation in the customer relationship and how it has been influenced by machine-based outputs.

As a research topic, the applications of AI in the fashion industry have been wide and intensively covered, according to Thomassey & Zeng (2018). Most existing literature on this topic aims to illustrate and explain the possibilities and advantages of AI in three main areas within the fashion industry: fashion sales forecasting, textile apparel manufacturing, and supply chain and garment design.

In this context, Leanne Luce (2019) explores AI through a fashion lens with the aim of creating an understandable guide for non-AI experts. Although the author dives into the AI components, from consumer-facing to fashion manufacturing, a perspective from the customer experience and the direct impact on the user behavior is lacking. Another general guide for AI in the fashion business is presented by Thomassey and Zeng (2018), which follows a commercial standpoint and focus on business and economic research in areas such as retailing, manufacturing, and sourcing.

More focused on the AI applicability is the work by Giri et al. (2019), which considers the impact of AI in the fashion and apparel industry, specifically throughout the supply chain.

The authors take into consideration several published articles to conduct their research, firstly categorizing them according to the AI tools, then proceeding to a classification based on supply chain stages and types of business (B2C or B2B). This work supports the premise in the beginning of this paper, where its conclusion points out the research gap from a B2C perspective, especially from a consumer-oriented archetype in the fashion industry.

Bonera and Corvi (2011) centered their research on the online buying process, by analyzing the influence of psycho-social variables in the online fashion purchase in e-commerce sites. Their conclusions, however, connect the utilitarian and hedonic shopping dimensions in the consumer experience to interactive web features, acknowledging vaguely the concept of technology and providing a narrowed approach to e-commerce platforms (in this case, websites). By expanding customer-centric research to multichannel experiences in fashion retail through a quantitative approach, Blázquez (2014) brought to light the influence of technology on perceptions and motivations of fashion consumers. Despite the contribution this research presented to the topic, the author indicates the importance of a qualitative inquiry to enrich the study of consumer experience, as well as the pertinence to focus on specific targets, since this research included a wide age and gender range.

None of the aforementioned works explore in depth the direct impact on the consumer or better yet, how the young fashion consumer is affected when being an active figure in an interactive process with data-based and AI-enabled techniques. Considering this gap, this dissertation intends to consider e-commerce AI-based approaches and to shine a light on how these technological techniques have been affecting the young consumer experience on e-commerce fashion platforms.

## **1.2. Research Questions and Objectives**

Based on this problem of investigation, the research questions were defined:

- a) How does AI unfold for the consumer experience in e-commerce fashion platforms?
- b) Does the interaction with AI tools condition the frequency of shopping online?
- c) How does AI perception in the observed online shopping experience affect the decision-making process of Gen-Z consumers?

Considering the subject of this study, the problem of investigation and the research questions, these are the specific objectives the following work will contemplate:

- a) To delineate the applicability of AI on user experience in e-commerce fashion platforms;
- b) To reveal if the frequency of shopping online is influenced by the interaction with AI tools;
- c) To illustrate how AI perception has repercussions on the decision-making process of the online consumer behavior, specifically Gen-Z consumers.

### **1.3. Research Overview**

The initial part of this dissertation, presented in Chapter II, intends to give a comprehensive theoretical approach on three main topic-related areas: AI, fashion e-commerce and consumer behavior, whereas the first is divided into two topics. The first topic brings a contextualization about the scope of AI and presents the most widespread techniques. Any professional, regarding the level of proficiency or employment industry extraneous to AI, can find this topic to be quite complex and difficult to understand. Although the main goal of this dissertation is not to educate on this subject, not even to be the primary source for those who want to learn more about AI concepts, it is important to provide context and foundational information in order to unravel the ubiquitous and powerful world of artificial intelligence.

The second topic displays the AI techniques that are implemented in the fashion industry. After exploring this field, it will be given an analysis of the fashion e-commerce and related business and technological development throughout the years, which will provide the unavoidable connection between AI and the fashion industry.

This framework ends with the consumer behavior, its theoretical background and the significance of technology and new media in this sphere. Understanding this subject is to consider a dynamic interaction between thoughts, feelings and behaviors, which can be somewhat challenging because the manifestation of cognitive and emotional responses is entirely dependent on how people articulate their thoughts and emotions, since these are not directly observable (Stephens, 2017). Moreover, for Bonera and Corvi (2011), customer satisfaction when purchasing a product or a service “comes not only from extrinsic reasons, but also from personal and emotional response linked to the pleasure of the purchase itself”, and this is applicable to both offline and online experiences.

Within consumer behavior in the context of new media, the younger consumer profile has been under the microscope for brands and researchers, as the opportunities to engage with this new generation of consumers has exponentially grown. According to We Are Social (2020), an annual research report conducted by Hootsuite, e-commerce adoption in any device is similar to every age group (from 16 to 64) and gender, a number which varies between 67.2% and 77.5%. Nonetheless, when scrutinizing these analytics, it is possible to pinpoint the importance of younger consumer generations, especially Generation Z and Millennials. In the “State of Fashion” report, written by McKinsey & Company in partnership with Business of Fashion (2019), both segments represent nearly 350\$ billions of “spending power” in the United States; additionally, the report predicts that, by 2020, 40% of global personal luxury goods consumers will be composed of Generation Z. Adding the fact this is the first truly digital generation, online purchases have become a natural habit – even if most of these young consumers are not financially autonomous (yet), they are gradually joining the workforce. So naturally, the digitally native youth could not remain unobtrusive when creating the profile of the online fashion consumer.

After the theoretical framework follows a mixed methods investigation in selected e-commerce fashion platforms to illustrate how AI impacts online consumer dynamics, particularly in a younger consumer profile. The investigation begins with a quantitative phase, where a survey was delivered to the participants hence a consumer's demographic and behavioral profile could be built. Afterwards, the qualitative phase takes place, with an observation experiment to disclose the participants' shopping behavior in selected AI-stimulated e-commerce fashion platforms, then followed by interviews to scrutinize the thoughts and feelings of the participants during the experiment. The development of an observation experiment will allow this investigation to obtain accurate information regarding the consumer behavior, since it documents the consumer's experiences during the consideration process, while simultaneously incorporating *touchpoints* – in this case, interactions with AI tools. More details about the methodology of this study are presented in Chapter III.

After the methodology, Chapter IV will contemplate the data collection and analysis of the results, which will eventually test the hypothesis and respond to the research questions. Overall conclusions, limitations, and future developments regarding the scope of this research will be covered in Chapter V of this dissertation. The outcome obtained through this study aims to give a pertinent conclusion to fashion companies about whether technological innovation directed to AI has been impacting positively or negatively throughout the consumer online experience.

## Chapter II. Theoretical Framework

### 2.1. Artificial Intelligence

#### 2.1.1. Definition and Context

For a nontechnical audience, AI is basically a field of computer science that approaches and recreates human intelligence in machines (Luce, 2019), recreating and automating human mental work into intelligent machines that can become capable of performing a variety of tasks, such as image recognition, memory recall, problem solving, etc. (Song et al., 2019). Because of its broader nature, it can be relevant to every industry but also more complex to understand and define its applications, although its development has been closely related and mutually influenced to computer technology (Song et al. 2019).

Also, because of the fast-paced emergence of Internet and consequently, the *information overload* that has evolved in what is known nowadays as big data, it has increased the necessity for companies to master and manage data flows in order to optimize their management and business decision making, whether is internally, between stakeholders or even competitors (Thomassey & Zeng, 2018). So, in that respect, AI approaches can be quite efficient and crucial, due to its ability in taking vast volumes of electronic formatted information (data) and transforming it into an accessible form for humans to consume it (Anand & Mobasher, 2005, p. 1). In this chapter, the concept of data and its derivations will not be explored in depth, as they are not entirely important for the purpose of this dissertation.

Understanding AI is also separating and distinguishing several application areas (Figure 1) from techniques and tools, also frequently mentioned in this field of study. Application areas refer to the specific areas where AI can be achieved and it can be extended to different industries (Long & Fox, 2002), whereas techniques and tools can be used across all application areas (Luce, 2019).

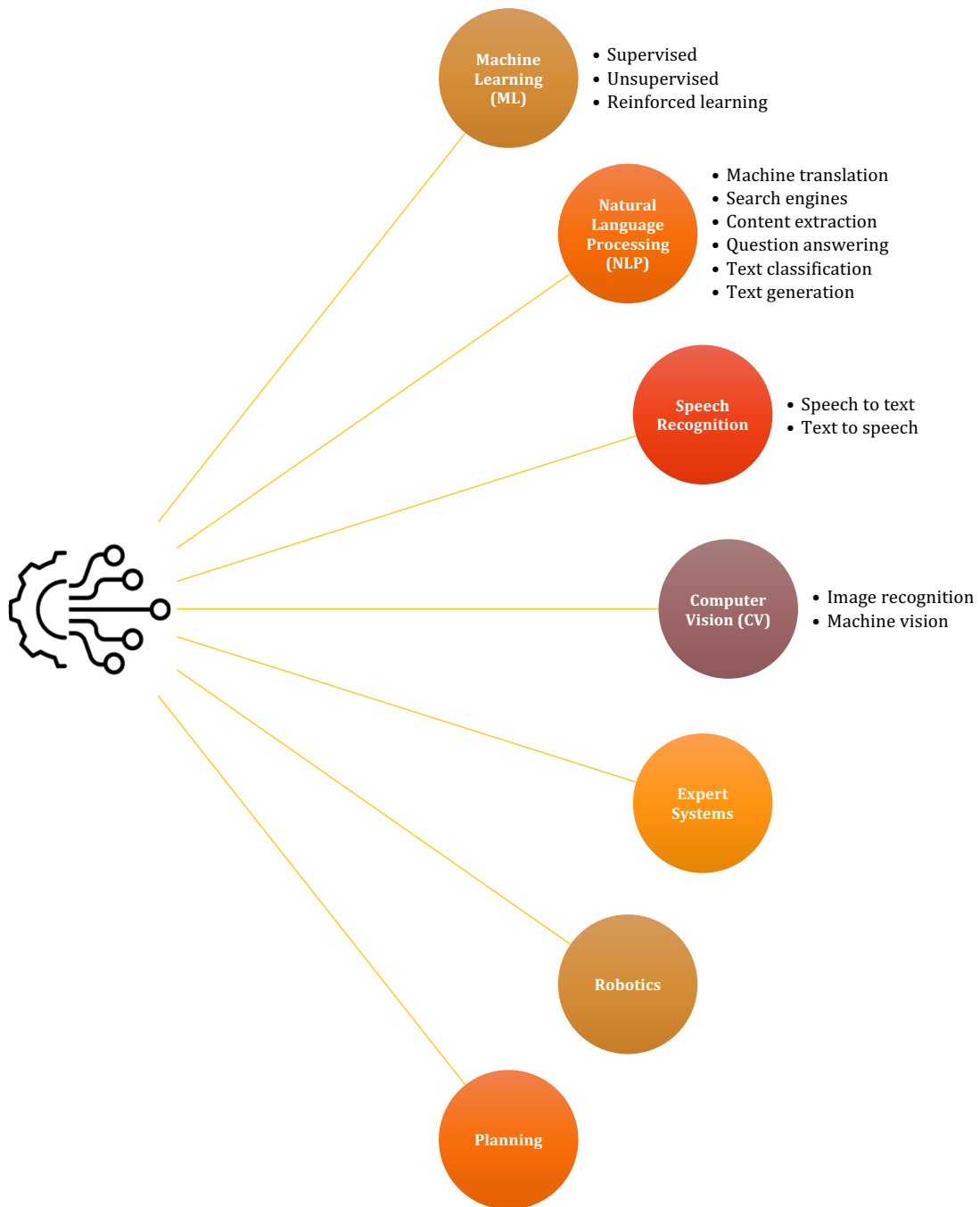


Figure 1. Definition of application areas and its ramifications within AI (adapted from Scientific American, 2002).

Some of the application areas and techniques will not be delved into due to its lack of relevancy to this research framework but also because later on, the techniques involved in the fashion industry will be explored in more detail. Moreover, some application areas like Machine Learning are so broad and ubiquitous that even though its direct impact on the user is hard to measure (escaping the entire purpose of this dissertation), an introduction to this field should be given.

### **2.1.2. Machine Learning**

One of the most mainstream concepts when talking about Computer Science is Machine Learning (ML), which is considered an interdisciplinary subject and application area within AI, involving pattern recognition, but also probability theory, statistics, and data mining, among others (Song et al., 2019). In fact, most application areas such as NLP, Computer Vision (CV) and Robotics, use machine learning based processes because it is the main factor to achieve AI. It is the machine learning component that enables an AI system to perform the following tasks (Mueller & Massaron, 2016):

- a) Adapt to new circumstances that the system was not originally programmed for;
- b) Detect new patterns;
- c) Create new behaviors based on the detected patterns;
- d) Make decisions according to the success or failure of previous behaviors.

When talking about ML, one must mention the concept of *algorithm*, which can be defined as a “procedure or a formula used to solve a problem” (Mueller & Massaron, 2016). Simplistically, the machine learns on its own the steps to achieve its defined target (goal) by training/gaining “experiences” (data/information), without being explicitly programmed. It is the algorithms that process this data through a series of well-defined, but not deterministic, states, in order to create an output able to solve the problem or achieve its target. The majority of businesses nowadays adopt machine learning processes, since its

goals are to decrease human effort by automating processes and consequently, discovering complex patterns human intelligence cannot detect and interpret by itself (Luce, 2019).

Inside ML, it is possible to identify three different categories (Figure 2): supervised learning, unsupervised learning, and reinforced learning (Mueller & Massaron, 2016). Although many versions of these terms can be found in research literature regarding this topic, these categories correspond to different ML algorithms. A concept that can be also found in computer science is Deep Learning (DL) which is a subcategory within ML algorithms that combines neural networks to perform these intelligent operations (Kamath et al., 2019).

- a) Supervised learning refers to when an outcome/target is labeled *a priori*, and the machine knows it corresponds to a given input through training. Classification problems (separation of data into groups with definite values) and regression problems (estimation of values or relationship between variables) belong to this first category;
- b) In unsupervised learning, there is no label in the data set, which means the outcome is unknown for the given inputs. It is only through patterns the machine can identify and form groups (clusters) of similar data;
- c) Reinforced learning is where a machine learns from past experiences, so its training consists of a trial-and-error method in order to make accurate decisions. Advanced technology used in chess games and autonomous vehicles can be found in this category.

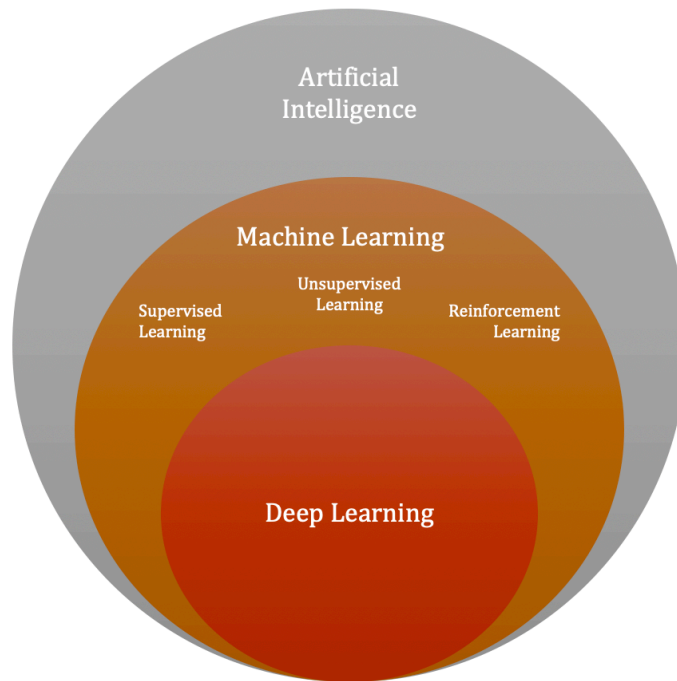


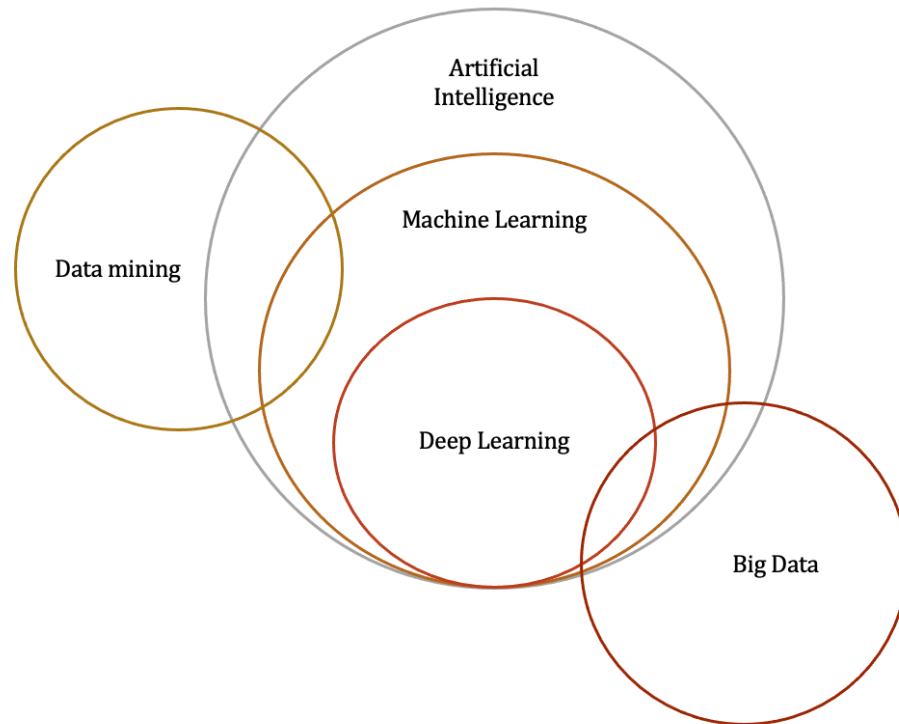
Figure 2. AI and its relationship with Machine Learning and Deep learning (Kamath et al, 2019).

The shift from an “analog” society to a “digital” during the last few years has had a significant impact on how people and organizations communicate and do business, with the omnipresence of digital information. In fact, to turn this available data into value for organizations, individuals and society, there needs to be a multidisciplinary field like data science to approach the complexity of inherent data processes, such as statistics, data mining, distributed systems and databases (van der Aalst, 2016). So, in this *big data era*, where human intelligence can no longer commensurate with the oversaturation of digital information, machine learning is necessary to process existent data to identify patterns and “predict the values of nonexistent data, often correlating to events happening in the future” (Luce, 2019, p.5).

These patterns, according to Luce (2019), usually translate into the discovery and definition of trends, which can be analyzed and modelled with algorithms so when facing certain inputs, machines are able to imitate human responses.

Within this perspective, data mining is the process that “extracts” (uncovers) meaningful and useful information from the immense and complex universe of big data so that later on patterns are disclosed and valuable insights are provided (Warwick, 2013).

Figure 3 can help to illustrate the relations between the terms previously mentioned regarding data and machine learning:



*Figure 3. The relationship between data and AI (Dey, 2019).*

### **2.1.3. Natural Language Processing (NLP)**

Natural language processing (NLP) is where human language and machine language converge and natural language is automatically manipulated (Kamath et al., 2019). Every piece of digital information users create because of interactions on the Web (text messages, social media contents, are some examples), contributes to the limitless expansion of unstructured, unorganized, and uncodified data (Luce, 2019). With NLP, it is possible to

understand and contextualize this data; also, the more accurate is the human language comprehension, the better the algorithm gets when making predictions – for that reason, it combines several fields such as computing and cognitive science, computational linguistics, and artificial intelligence.

However, the ambiguity and unrestrictive nature that often characterize natural language, specifically written, can still be a major obstacle when it comes to the efficiency of an NLP method (Nadkarni et al., 2011). According to Jacob Eisenstein (2019), the most used and visible embedded applications in the past decade include: automatic machine translation on the web and in social media; search engines with a high level of linguistic sophistication; content extraction, also known as *named entity recognition* (NER), that automatically identifies and categorizes specific words/information in a text (Nadkarni et al., 2011); question answering systems, which include text-only interfaces and spoken dialog systems such as today's virtual personal assistants (VPAs), like Amazon's Alexa or Apple's Siri; text classification that can be materialized in spam detection on email inboxes; and text generation, or Natural Language Generation, where the idea is to use machine learning fundamentals to generate sentences in text (Kamath et al., 2019).

The way people interact and communicate with the world through AI devices has come a long way, as a result of important developments in computational linguistics and machine learning (Khillar, 2020). For that reason, it is important to distinguish NLP from speech recognition, often used in this field of research. Although these concepts seem relatively identical, speech recognition is an automation process within technology that identifies and understands spoken language (words or sentences) and converts it into "machine readable format" (Khillar, 2020). Although it deals with spoken inputs, this type of technology does not understand the meaning or the context of such inputs. On the other hand, NLP is a field of computer science where machines are able to process and understand human languages in order to perform useful tasks involving "computer-human interaction" (Mueller & Massaron, 2016).

#### **2.1.4. Computer Vision**

While NLP deals with the complexity of languages and verbal communication, Computer Vision (CV) is the AI field that takes out images and videos to process and analyze, resembling the human visual system (Luce, 2019). The visual information (analogical object) is captured and analyzed by a camera and a digital signal process method which transforms it into a digital object. However, human visual systems, unlike machine vision, can perceive the three-dimensional reality and identify its properties with apparent ease (although optical illusions can still deceive human's vision and perception), such as illumination, shape, and color distributions (Szeliski, 2010).

For that reason, mathematical techniques, specifically physics-based and probabilistic models, have been developed in parallel with computer vision models in order to recover the three-dimensional characteristics of objects in image recognition and consequently, solve some of the complexity of its practical tasks (Szeliski, 2010) – a correct and contextualized interpretation of an image, given insufficient information, for example. In today's context, for Kevin Warwick (2012), the field of study regarding AI vision is still at a very early stage and this is mainly explained by the late technological developments of cameras, which are “machine-based versions of the human eye”, as they are becoming more precise, smaller, and cheaper. So, in that regard, it is normal that most of the methods and applications in this field are still in a research phase, and those that have found their way in real-life applications, are often task-specific and specialized in “solving well-defined computer vision problems” (Warwick, 2013, p. 147).

#### **2.1.5. Expert Systems**

Expert systems are considered to be one of the initial approaches to AI, within the first successful forms of technological software. The concept behind this type of software was to recreate knowledge about a specific domain and to be able to work on it, similar to the expertise of a human professional (Warwick, 2013). In practical terms, the knowledge base about that domain would have to be generated and inserted by the expert, using specific

rules they would provide in order for the software to follow, so the non-expert user could receive advice or explanations regarding the inputs he had inserted in the user interface (Thomassey & Zeng, 2018), as shown in Figure 4:

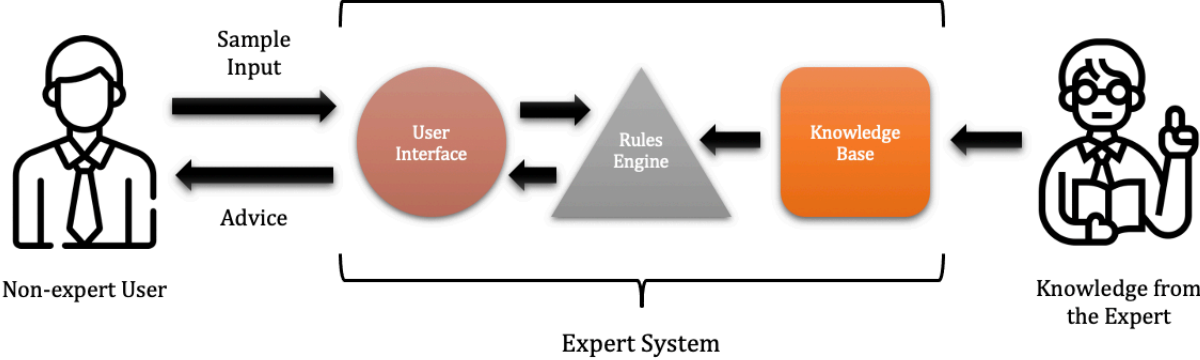


Figure 4. Components of an Expert System (adapted from Warwick, 2013).

This type of software can be widely found in medical systems, used primarily for diagnosis, but there are several areas where expert systems can be easily recognized: in autonomous driving technology (Eliot, 2018), in schedule management software, accounting, coding, and even in gaming environment (Metaxiotis et al., 2002). Nowadays, with the advances in machine learning and neural networks, expert systems are reaching a new level of capability in computing power (Eliot, 2018).

**2.1.6. Robotics**

This has been considered one of the “most exciting developments” in the history and current state-of-art of AI technology (Warwick, 2013), where topics such as artificial life, biologically inspired techniques and collective intelligence have been discussed and amplified, not only in science and engineering but also in art and philosophy. Simplistically, robotics is the field focused on the design and manufacturing of robots with the purpose of assisting humans in performing more difficult tasks or with a more consistent approach. A

robot can also be considered the “embodiment of an artificially intelligent entity”, so if AI is the brain, the robot is the mechanical body (Warwick, 2013, p. 116). The well-known example of this symbiosis is *Sophia*, the humanoid robot unveiled in 2016, considered a trailblazer in social robotics and a successful prototype of robotics and machine learning combined (Hennessy, 2021).

According to Jim Torresen (2018), member of the Norwegian Academy of Technological Sciences (NTVA), the unpredictability of the future and the potentiality of technology have always inspired fiction authors and cinema in creating exciting scenarios, with past examples such as Jules Gabriel Verne (1828-1905), considered nowadays as the father of science fiction, or even dystopian scenarios such as Fritz Lang’s *Metropolis*, the cinematographic masterpiece launched in 1927. These examples illustrate the dichotomic approach that divides researchers when it comes to technological progress (positive and optimistic contributions vs. negative impacts on society and mankind), which emphasize the importance of ethical aspects of technology in the discussion (Torresen, 2018). Nevertheless, there seems to be a consensus about the continuous growth of investment in robotics in the near future and as long as the progress in AI research continues to impact intelligent robots and autonomous systems, many industries can expect widespread exploitation (Shaw, 2019).

When it comes to the technologies within robotics and its multifaceted purposes, a distinct categorization can be provided (Torresen, 2018):

- a) Industrial robots, used for several years in manufacturing for aerospace, automotive, and other industries that involve a “number of degrees of freedom” and a human programmer;
- b) Service robots, which are currently seen in selected settings to perform useful tasks in a semi or fully autonomous operation, such as internal transportation inside public facilities (e.g., hospitals), or domestic operations (e.g., vacuum cleaning).

### **2.1.7. Planning**

When talking about automation in AI, one must mention the field of Planning. This is the ability to use stored information to draw a sequence of procedures (conclusions) in near real time, in order to solve a problem and/or reach its goals (Mueller & Massaron, 2016). This technology is equivalent to the human intelligence behavior in reasoning about actions, where technological systems replicate the intelligent effort around the deliberation on how to proceed towards seeking a goal or solving a problem, whether it is a familiar or unfamiliar situation (Wilkins, 1990).

Although this generic reasoning can be applied into a broad spectrum of areas and mechanisms, it has become clear that its efficiency relies on the definition of more specific problem-solving and goal seeking reasoning, therefore, creating several specific sub-fields within AI Planning throughout the last decades (Long & Fox, 2002). But on its core, the starting point for an effective and manageable planning process must be a precise definition of what constitutes the problem and what solution could be consequently applied: fundamentally, the process accounts for a collection of actions, each with their own preconditions (valuables that must be established “in order for the action to be executed”), their postconditions (“which describe the effect of execution of the action”), a contextualization of the situation and ultimately, a “description of the goals to be achieved” (Long & Fox, 2002).

AI Planning research has come a long way since its earliest days, and while much progress has been accomplished, simulations of real-life planning problems are still considered quite complex; in fact, most of its constraints reflect on the difficulty of representation and reasoning about time and causality and other factors (physical or abstract, like sensations) related to unpredictability and uncertainty that are inherent in the real world (Hendler et al., 1990). Nevertheless, there have been some modern planning approaches that can effectively overcome some of the constraints, such as heuristic search planning, which evaluates alternative possible routes within the initial course of actions (“plan”) that can be automatically generated and ultimately redefine or modify the plan, while maintaining the speed timeline (Long & Fox, 2002).

## 2.2. Artificial Intelligence in Fashion

After unraveling the world of AI, it is time to sharpen the foundational framework into the fashion industry and reveal the inner applications through the segments of the fashion value chain. As mentioned before, AI is a wide field that has been covered by several industries throughout the years. The “democratizing effect” as a result of the development of the powerful computing, big data and DL, has been altering business models and contributing to a major technology expansion overall, not excluding the fashion industry (Abnett, 2016).

The presence of AI in fashion is most noticeable and relevant in the supply chain management, personal customer service and design and clothing production (Abnett, 2016), since that is where the opportunities of growth rely on the most. A variety of AI techniques and tools also have been successfully applied in the apparel manufacturing industry, including genetic algorithms (GAs), artificial neural networks (ANNs), fuzzy set theory, and others within machine learning (Jelil, 2018), such as generative adversarial networks (GANs) or predictive analytics (Luce, 2019). These techniques have been proven to be the most suitable and effective in the fashion industry due to their capacity do deal with complex correlations and dependencies within data and uncertainties related to human factors, such as consumer behavior, designers and professionals’ knowledge, sensory quality attributes, among others (Thomassey & Zeng, 2018).

Nevertheless, it is possible to recognize and categorize some of the mainstream AI tools known to the everyday customer within the fashion industry (Figure 5):

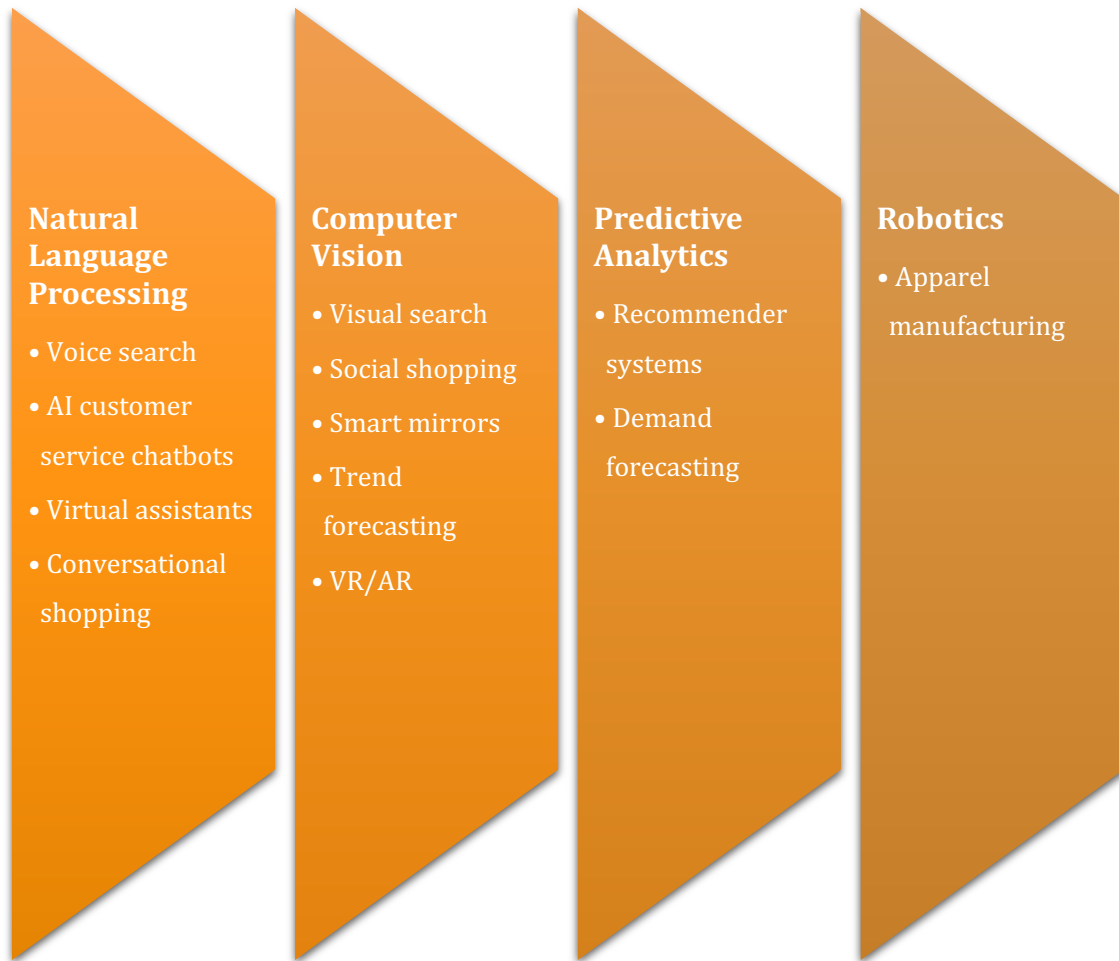


Figure 5. Systematization of the mainstream AI application areas and its tools within the fashion industry (Luce, 2019).

A few of these AI tools can be found in e-commerce and digital platforms, whereas most of them combine different foundational concepts, such as databases and machine learning (Luce, 2019). Contrary to what happens in a fashion retail environment, where the customer is exposed to what it seems an infinite choice, the ability to create a customized selection and a personalized experience is only possible by collecting data, and this is what has been stepping up the game for e-commerce transactions, making AI a driving force in this matter (Song et al., 2019).

### **2.2.1. Genetic Algorithms (GAs)**

As an approach to evolutionary computing, GAs are algorithms of heuristic search based on the principles of natural selection, where each member of a population has a unique genetic code that, combined, forms a string of computer chromosomes (Warwick, 2013). Similar to the biological process, a new generation is created by the mixture between the chromosomes from two different individuals, preferably the fittest ones so it can inherit the characteristics of its predecessors, and this reproduction process goes on until a generation with the fittest individuals is found. This analogy can be applied in a problem search approach: a set of solutions (individuals) for a problem are considered, within a range of characteristics, and the fittest ones are selected in order to achieve a solution (Warwick, 2013). In fashion, this technique has been proposed in earlier literature to solve production scheduling and planning method problems in clothing manufacturing processes (Wong & Chan, 2001).

### **2.2.2. Artificial Neural Networks (ANNs)**

The genesis of AI has always been the recreation of human capabilities, narrowing from genetics and biology to neurological systems and brain functions. The human mind as a model of intelligence (Luce, 2019) is a reference point in AI technology, and ANNs are a practical example of that. The structure of a biological neuron network and its method of learning is the core of ANN, where the aim is to employ technological means to materialize the characteristics of the biological neuron (Warwick, 2013). These characteristics were based on the composition model of a previous understanding of the behavior of biological neurons: a single neuron would take in input, process it and then send an output (Luce, 2019). Training is also an important step of this implementation process, because ultimately, the efficiency of modern AI technology and its main purpose relies on the ability to be aware of a situation and adapt from previously learnt experiences (Warwick, 2013).

In fashion literature, ANNs were the first model to be studied and employed for fashion retail sales forecasting. Although the ANN-based methods have a great performance in

forecasting accuracy, these require a more extensive training model (Ren et al., 2018), becoming, consequently, more time consuming when it comes to completing the forecasting task. Other applications of this AI tool can be found in demand forecasts as well (Rodrigues & Figueiredo, 2013), and in clothing manufacturing, with the purpose of predicting potential problems (Hui et al., 2007).

### **2.2.3. Fuzzy Set Theory**

Inserted in the interweaving between mathematics and evolutionary programming, fuzzy set theory is a mathematical model “in which vague conceptual phenomena can be precisely and rigorously studied” (Zimmermann, 2011, p. 6). The fuzzy model is mostly associated with expert systems, because of its ability to incorporate human knowledge for inferencing decision making and provide the uncertainty factor (Warwick, 2013) – the grey shade in apparent “black and white” scenarios. The premise of the fuzzy logic (or *fuzziness*) comes from the uncertainty and vagueness that real-world situations often bring to humans and the degree-vagueness originated in the interpretation of those situations that usually generate outcomes with a fair degree of probability (Zimmermann, 2011). So, in certain circumstances or after a series of facts, it is useful to have conclusions that can be partially true or have a “confidence percentage to be applied to results” (Warwick, 2013, p. 39).

The fuzzy techniques can be found in several science-related fields, such as engineering, medicine and meteorology, in which human judgement, involving decision making, reasoning and learning, are mainly present (Zimmermann, 2011). In fashion, it has been primarily proposed in sales and demand forecasting systems, in scenarios of forecasting sales of new fashion products in the market in which there are few or non-existent historical data, although applied with other techniques such as ANNs, especially under a big data environment where time and efficiency can sometimes become compromised (Ren et al., 2018). Also, another interesting application can be to predict clothing sensory comfort, where the fuzzy technique can be an alternative to the traditional statistics models when dealing with the complex relationship between mechanical properties of apparel fabrics and

sensory data. In general, garment manufacturing and product designing have also been incorporating this technique with innovative expert systems, combining professional knowledge and consumer preference (Jelil, 2018).

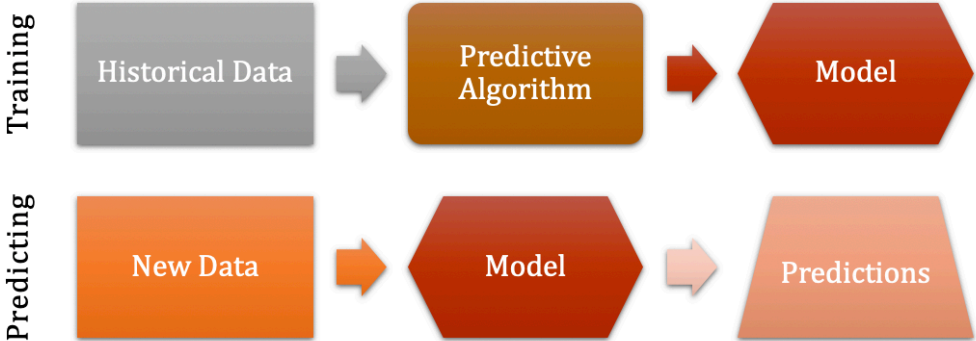
#### **2.2.4. Generative Adversarial Networks (GANs)**

Generative modeling is one of the most promising technologies within machine learning that was created to increase the efficiency of unsupervised learning and deliver better results in terms of statistics and probability (Pan et al., 2019). Using GANs, this type of model can automatically discover and find regularities or patterns in input data and consequently generate new examples that “plausibly could have been drawn from the original dataset” (Brownlee, 2019). For this function, there are two networks involved in GANs: the generator, used to create results based on realistic data, and the discriminator, which evaluates the accuracy of the results and distinguishes fake examples (generated) from real examples (from the domain) (Pan et al., 2019).

Two practical examples of this model can be found in image-to-image translation problematics, where new and unique images can be created from a dataset of images, or it can fill in missing information from images that are damaged or incomplete (Luce, 2019). The first example is what had been on the genesis of Amazon’s first *AI Fashion Designer*, the first algorithmic approach to fashion and apparel design by the retail brand (Knight, 2017): the model internalizes the properties of a particular piece or style, by processing a dataset of images, hence applying that style to create a new item of clothing. Although a computer-based fashion designer still has several limitations, GANs can hold other potential when it comes to garment manufacturing: aiding fashion designers with graphics generation or “automatic mapping of 2D images of garments onto images of people” (Luce, 2019, p. 126).

**2.2.5. Predictive Analytics**

As mentioned before, data mining is the process in machine learning that uncovers useful information in a vast universe of data. Part of this “useful information” are valuable insights or historical information conveniently used to predict events that can happen in the future. The methods set up for this operation, situating between statistics and machine learning, exist within predictive analytics (Luce, 2019). Just like other machine learning techniques, predictive analytics wields an algorithm (a statistical method) with two different stages, training and predicting (Figure 6):



*Figure 6. The training process within predictive analytics (Luce, 2019).*

Most of the distinct areas where predictive analytics have been put into action are related to sales forecasting. Like the fashion industry, customer-oriented markets thrive on corresponding accurately and rapidly to (uncertain) demands, while facing arduous challenges such as short life cycles and a lack of historical sales data, because production plans must be placed before “exact knowledge about future demands is available” (Beheshti-Kashi, 2014, p. 154). In this regard, recommender systems and demand forecasting (Luce, 2019) are two distinguishable examples that most fashion companies depend on to get around the irregular consumer behavior patterns and high variability of fashion sales data (Choi et al., 2011).

### **2.2.6. Named Entity Recognition (NER)**

It is part of one of NLP's techniques. As previously mentioned, NER refers to the methods of content extraction within data processing that identify specific words and nouns ("entities") and classify them into categories such as peoples, organizations and locations. Because this technique deals with the ambiguity of natural language and reuse of words, the precision and the accuracy of the categorization are sometimes compromised (Kamath et al., 2019).

However, NER can still be quite helpful when it comes to the study of marketing strategies on social media: authors Jorge Alé Chilet, Cuicui Chen and Yusan Lin conducted a study in 2016, which aimed to analyze social media marketing of high-end fashion industry, using NER to focus on the informational content of different high-end fashion brands on Instagram (Chilet et al., 2016).

## **2.3. Fashion E-commerce**

### **2.3.1. Current Status**

As stated by Guercini et al. (2018), the incredible development the fashion industry had been witnessing within the electronic trade of fashion products in recent years has contributed to an emergence of new marketing models and consequently, new tools. The impact of new ITs, the integration of offline and online marketing strategies, the role of new players in the marketing panorama such as influencers and fashion bloggers, and the highly competitive market; all of these consist of big factors for a new marketing approach in fashion e-commerce. Ultimately, and according to the same authors, it is technology and consumer behavior that "effectively drive this new marketing approach" (Guercini et al., 2018, p. 5).

When talking about the current shifting of the fashion marketing approaches, one must mention the impact of the coronavirus pandemic that disrupted in early 2020. The humanitarian and financial consequences brought up by the pandemic have revealed a disorientating future and pessimistic predictions about a normal and stable daily-life environment within the next year, at least. Also, worldwide industries are still focusing on contingency planning and crisis management strategies, as a result of the fragmented financial markets, dismantled supply chains and an overall diminished consumer demand (Amed et al., 2020). However, according to Business of Fashion (2021), there are two predictive scenarios for the global economy: the first optimistic scenario estimates that the global economy could recover its levels of activity (similar to 2019 values) by the third or last quarter of 2021, but with different growth trajectories across regions; the opposed pessimistic scenario assumes recovery in businesses still has a long path and they will experience a “continued volatility in supply and demand for multiple years” (Amed et al., 2020, p. 17). Nevertheless, restructured business and marketing models will be expected for the several years ahead.

### **2.3.2. Marketing and Sales Channels**

One discussion that had been recently resurfaced when it comes to marketing models is the role of direct-to-consumer (DTC) channels vs. the wholesale channels (Fernandez, 2021). In the case study “The New Four Ps of DTC Marketing”, published by Business of Fashion (Mondalek, 2021), the author underlines the importance of renovation in the matured and stagnated DTC market, as well as the necessity to improve marketing and business approaches in the post-pandemic reality. In this sense, the proposal of the “Four Ps” (also known as “marketing mix”, it is a marketing set of principles that refers to *Product, Price, Place* and *Promotion*), is switched up to:

- a) Purpose: which corresponds to a values-driven approach;
- b) Positioning: a brand culture defined by marketing narratives and experiences;
- c) Partnerships: collaborations with brands with a complementing strategy;

d) Personalization: custom-made offer of products and experiences.

A strategy guided by these principles while investing in a transparent communication, an effective paid social media ad and a multichannel experience can deliver the right results in terms of profit and consumer's loyalty (Mondalek, 2021). This strategy, however, implies a great amount of investment and not every fashion brand has the capability to afford it, since it is more expensive to acquire a customer base through direct channels and to support productions, logistics, delivery, and customer service costs (Sherman, 2020).

Meanwhile, relying on wholesale strategies or online marketplaces can offset some of the heavy costs surrounding direct channels (Sherman, 2020). Fashion brands choose to invest in these channels because it gives them wider online exposure and makes it easier for consumers to discover and purchase the brand's products, while still having control of their products (Fernandez, 2021). Furthermore, online marketplaces have the advantage to provide brands the possibility to use the same stock inventory as for their own direct channels, but sometimes the business deal comes with a consignment sales agreement, where the brand only gets paid once its products have been sold (Sherman, 2020). As a result, choosing the right marketing channel or balancing the right sales channels is a strategic challenge for most fashion brands, one that the pandemic has not made it easier (Fernandez, 2021).

### **2.3.3. New Players in Fashion E-commerce**

The importance of new information technologies and its implementation in supply chain management (SCM) is sustained by the global dimension of most supply chains within the fashion industry, since most brands and enterprises have customer demand coming from different international locations (Lo & Hong, 2012). Besides the expensive cost of implementing and building an information system, most companies, even small and medium enterprises (SMEs), choose to invest in these because, regardless of the economic environment, satisfying customer orders while optimizing production and manufacturing costs is always the key for a successful business, as authors Wei-Shuo Lo and Tzung-Pei Hong

stated (2012). So, the goal of information and communication technologies is to gather and analyze information on market players, as well as on current and potential customers in order to support the development of products and services with a higher chance to correspond to demand, as well selling through the right channels and platforms (Meler & Stormer, 2009). Within the SCM, information technology can assume several functions (Lo & Hong, 2012):

- a) Supply: tasks related to sourcing, purchasing, and transporting raw materials; also handling parts of inventory; making deliveries. These tasks are part of what is called *inbound logistics*.
- b) Operation: tasks related to the processes of production, mainly production planning, scheduling, and process inventory.
- c) Distribution: tasks focused on satisfying customer requirements, such as demand forecasting, customer service, finished goods inventory, warehousing, and transportation. These tasks are part of what is called *outbound logistics*.

It is clear that e-retailing, and consequently e-commerce, are key elements for international business growth, particularly in fashion. In fact, fashion products represent a significant category within global e-commerce, and since most fashion businesses have already achieved an internationalization process, the use of the Internet and effective online channels are important tools in potentializing such processes (Guercini et al., 2018). Although the store environment and offline marketing strategies are still valuable assets for fashion brands, besides the step back during the global pandemic, the digital customer journey can no longer be neglected if fashion brands want to thrive and stand out in this ever more competitive and homogenized market (Amed et al., 2020). Omnichannel ecosystems are a new reality in fashion retail, integrating both online and offline strategies, whether it is in business, through inventory management, logistics, and even customer service (Guercini et al., 2018); or in marketing, wherein new tools are being implemented to excite and encourage customers to engage with brands online.

Recently, digital innovations in the omnichannel strategies have been providing creative solutions to design and marketing departments, who have been able to successfully integrate

human interaction into the digital experience: livestream commerce, for example, had been a trend in the Chinese fashion market, that started in 2016 with the online retailer mogul Alibaba, and nowadays it has reached luxury brands such as Burberry or Ralph Lauren. Besides the integration of human interaction into the digital experience, AI has also been playing a prominent role in the digital customer journey, with tools such as virtual try-ons powered by AR (Amed et al., 2020); indeed, as reported by Shopify, conversion rates on e-commerce websites increased by 250 percent on products supported by AR technology (Briedis et al., 2020).

In this context, influencers have also been a valuable contribution to influence consumer behavior and increase conversion rates through these omnichannel strategies that combine storytelling with an integrated digital experience. In some cases, influencers were even able to generate more sales in a couple of hours than department stores in a full day (Amed et al., 2020). In truth, over the years, fashion bloggers and influencers have been gaining a remarkable status in the fashion business, specifically due to their influential impact to generate trust and credibility and to influence purchase decisions (SanMiguel & Sádaba, 2018). For fashion brands, an investment in influencer marketing has been commonplace in communication and marketing strategies because fashion bloggers and influencers are seen as opinion leaders, taking their readers to, not only trusting their judgement, but also considering them as reliable sources of information and advice within fashion-related topics, and lead examples in fashion behavior, social acceptance, and innovative matters (SanMiguel & Sádaba, 2018).

## **2.4. Consumer Behavior**

### **2.4.1. Theoretical Approach**

With the emergence of IoT and the rise of new forms of social media spaces, the importance of the online involvement in the consumer behavior, particularly young

consumers, has become a pertinent and significant field of research by itself, with research showing that web experience interferes with mental processes that ultimately influence the online buying decision (Cetină et al., 2012). Before addressing the young consumer profile, some contextualization of the research pragmatism should be depicted.

In awareness of these mutations in the research of the online consumer behavior, *netnography* is a type of ethnographic methodology that has gained popularity among marketing researchers, focused on online consumer communities where the investigator usually chooses a participative yet noninfluencing approach in observing and collecting insights regarding interests and opinions about specific products, brands, or activities, sometimes including an offline environment observation.

Although the human presence in these types of study seem to be quintessential, the nonparticipatory (passive) approaches have also been adopted in certain environments involving risky or sensitive matters since it ensures the natural context of the community and does not influence any result afterwards (Costello et al., 2017). Despite the preferred research approach, most studies regarding this method have identified the importance of online communities' dynamics and how they have been gaining major influence in the consumer decision process, that goes beyond consumption decisions, affecting mostly the problem-solving process (Wang et al., 2021), and its main five stages: need/problem recognition, information search, evaluation of alternatives (also known as consideration stage), purchase decision and post-purchase decision (Masterson and Pickton, 2014). However, this is a very flexible and dynamic process where consumers do not always follow this exact five-stage decision process, or even move in the same order: the evaluation stage may sometimes finish with withdraw and the purchase never happens; the second (information search) and third stages (evaluation) can be repeated several times; and for low-involvement/impulsive buying/frequently purchased products, there is no or little effort from the consumer in engaging in external search or evaluation of alternatives (Stankevich, 2017).

Social learning (SL) research, regarding more traditional methods such as observational learning (OL) and word-of-mouth learning (WOML), has been conducted in the study of the

market behavior and in the foundation of theoretical background regarding consumer decision process, concomitantly with the sustained literature of consumers' cognitive learning (Wang et al., 2021), and behavioral learning (Rath et al., 2016). Learning, in this sense, can be described as the "change of behaviour as a result of gaining new knowledge and experience" (Batkoska & Koseska, 2012, p. 71). Both previous processes interfere with the decision-making process, although direct effects of each process are visible in different stages:

- a) Cognitive learning is a complex mental process of consumer-related cognitive activities with the main purpose of solving purchase problems or fulfilling needs, including "learning of ideas, concepts, attitudes and reasoning abilities" that ultimately transform this stored information (memory) into knowledge that could be used in current and future behaviors. This process is especially important as a motivator of the consumer reaction and the consumer behavior in general (Batkoska & Koseska, 2012).
- b) Behavioral learning follows the experiments developed by physiologist Ivan Pavlov and consists of a learning process through exposure to external stimuli. This process occurs when consumers respond to certain stimuli, and it can be unconsciously conditioned (*classical conditioning theory*), or it can be derived from the pursuit of a reward over a selection of options (*instrumental conditioning theory*), and consequently reinforce the behavior (Rath et al., 2016);
- c) Social learning is the process that revolves around social interaction. In this personal learning process, the information selected by others (family, friends, and reference individuals/groups), whether by observing behaviors or searching for others' advice and suggestions, is considered to be more important than what oneself may have collected. For the stages of product search, evaluation, and purchase decisions in the online shopping behavior, this process has been proved to be highly impactful (Wang et al., 2021).

A visual representation (Figure 7) will help understanding the relation and the dynamics of the concepts previously mentioned:

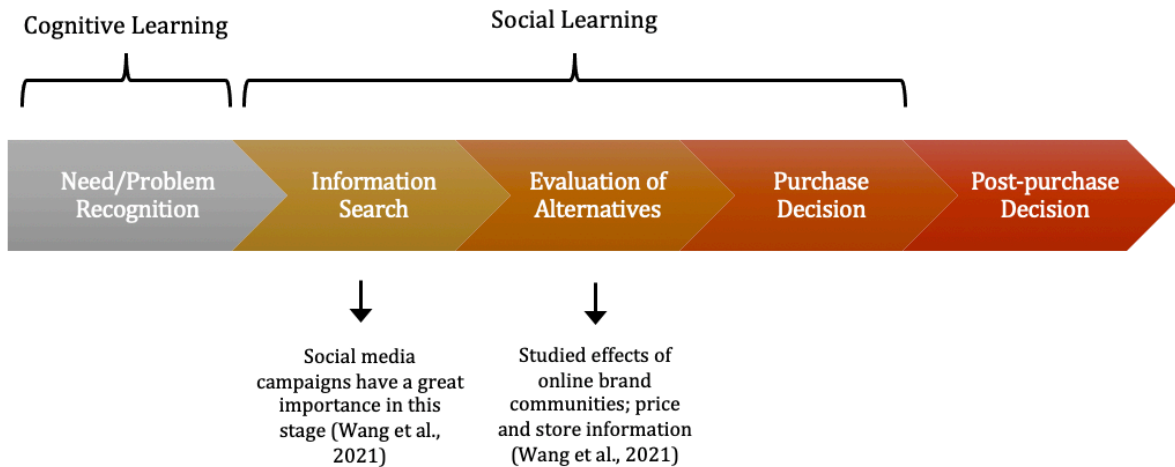


Figure 7. Decision-making process and the impact of the learning processes.

Even though these stages are common for every individual, the way each consumer makes their own decision is distinctive. Three different decision-making approaches can be introduced to reflect this reality (Rath et al., 2016):

- a) Rational approach consists of a logically based thinking process. These analytical consumers take their time to learn, collect and process information and after carefully evaluating the pros and cons, they make the best decision. Because this is a conscious thought process, the “distractions” of a store experience and environment are not easily alluring for these consumers;
- b) Behavioral approach combines the behavioral learning process with decision-making where consumers’ actions are learned in response to specific stimuli. Automatic or frequent responses used to make or even improve judgements or choices are part of this theoretical framework;
- c) Experiential approach derives from the *gestalt psychology* theories, in which there is a creation of meanings from the stimuli perceived. This perceptual organization is a result of the beliefs, values, behaviors, and personal perspectives that influence the overall experience of decision-making.

It is important to note these approaches mainly focus on the perspective of the decision-making style, excluding other decision-making characteristics that also affect the purchase decisions. Individual characteristics, such as demographics and product/brand knowledge; product-related characteristics like product involvement, and technological tools also play an important role in the impact of the decision-making processes (Karimi et al., 2015).

Social media, for example, has been shifting the communication paradigm, not only for social interactions between users but also how businesses spread their messages and listen to their consumers (Cao et al., 2014). Virtual interactions on social media not only allow users to view and share a wide variety of information, but from a social perspective, users are able to create online personas, where they perceive themselves with similar attitudes and behaviors as their peers, which also enhances their sense of belonging to an online or brand community (Xiang et al., 2016), therefore reshaping their entire online consumer behavior. The effects of word-of-mouth have been proved highly effective in affecting consumer's attitudes and influencing purchase decisions, so it is no surprise that social media have an astounding impact on the different stages of the decision-making process, "particularly as a source of inspiration and for the evaluation of alternatives" (Cao et al., 2014, p. 80).

#### **2.4.2. Generation Z Profile**

In this regard, the option to focus on the Gen-Z consumer profile (aged 18-25) was not accidental. Besides the fact that, as stated in the report "Gen Z and Millennials 2020" by Drapers (2020), Gen Z were predicted to account for 40% of global consumers by 2020, and there is no slowing down for them to "represent a powerful and influential majority of retailer's consumers for the coming decade". In the same report, it is mentioned that online stores are the main preference to shop for fashion for these consumers, and this option is mainly driven by convenience, the search for the best price, and the relaxed and fun experience that these digital platforms can provide. Another interesting insight about this report is that "better fit technology", "better images" and "styling advice" are amongst the

most voted attributes that fashion brands and retailers should deliver and invest in their e-commerce platforms.

According to the case study “Gen-Z Shopping: Separating Myth from Reality”, from Business of Fashion (2020), the also known as “digital natives” are a powerful source to fuel higher rates of consumption, and fashion is no exception: in practice, these youngsters want fashion brands, not only reflect their values and beliefs but also “to act as an extension of them”. So in this sense, they sometimes can be perceived as capricious when, in fact, they just want brands to speak their language and deliver a “singular, cohesive aesthetic, value or sense of cultural credibility”, one that respect social movements and fluidity dynamics. Nowadays, because the reality of consumption is based on omnichannel strategies, with multiple digital and physical platforms and mediums that intersect in a constant and emotionally engaged dialogue, young consumers are more informed and consequently have more independence and authority regarding their purchase decisions. However, it is still clear how social media and brand values are still a major force of influence in their spending habits.

These two reports not only served the purpose to illustrate the teenager profile much needed for this dissertation, but it also came to show that the behavioral dynamics is in line with this research topic and its purpose.

## Chapter III. Methodology

### 3.1. Mixed Methods Research

After the study of the topics presented in the theoretical framework, an empirical research based on netnographic methodologies was conducted to demonstrate the application of AI technology and its effects to the consumer in digital fashion platforms (apps and websites).

This research was based on the Convergent Mixed Methods Design (Creswell & Creswell, 2018), a mixed methods approach that combined quantitative data, such as psychographics and behavioral data, from a questionnaire with qualitative data, based on a netnography research, gathered from a participant observation of the online consumer behavior which underpinned the interviews to extract insights about the participants' experience. Although netnography practices are mostly applied within social media spaces and online communities, the research procedures can be adapted according to the investigator's intentions and combined with other research methodologies, as long as there is a human presence in netnographic enquiry (Costello et al., 2017). During the participant observation, it was also implemented the *think-aloud protocol*, a type of research usually used in usability tests, in order to gain insights into participants' feelings and thoughts during the tasks performance (Cooke, 2010). This implies that when performing a set of tasks, participants have to verbalize whatever crosses their mind. Even though these types of verbalizations alone are insufficient to provide a complete picture of the user experience, hence the importance of combining with other types of research, they are often accurate and insightful (Cooke, 2010).

The key idea of this methodology was to collect both forms of data while using parallel variables and concepts, so at the end certain themes could be associated with statistical data. The same number of participants were used on both the quantitative and qualitative methods. The configuration of this methodology can be seen on Figure 8:



Figure 8. Convergent Mixed Methods One-phase Design (adapted from Creswell & Creswell, 2018).

### 3.2. Data Collection Methods

Based on the Convergent Mixed Methods, the data collection methods consisted of quantitative and qualitative approaches, where data was collected using the following tools: questionnaires, participant observation, and interviews. All investigation tools were tested a week before starting this study, whereas two partakers were chosen to detect any comprehension issue or mistake. After confirming that all the tools were ready to be submitted and implemented, the study could start. A systematic random sampling that took place on social media (*Instagram*) was used to select participants aged 18-25 years old. From 37 users that were impacted, 21 responded with interest. But within this number, only 57% of the contacts resulted in successful follow-up. What is also important to note is that, after the collection and analysis of the data (see Chapter IV), more participants were not sought because the recurrence of the same patterns was observed in the tests.

Ahead of the methods, it was necessary to undertake risk assessment in the light of the principles of research ethics (Denscombe, 2012). In this case, participation in this investigation was completely voluntary, and once the participants decided to take part, an informed consent document was sent by email (which they had to read and sign), providing detailed information about the purposes of the research, the nature of their involvement (the choice to whether or not to participate) and further implications about the data collected. The informed consent document can be found in Appendix I.

After signing the written informed consent form, the data collection process was set in motion. Firstly, the participants had to fill in a questionnaire regarding demographics and previous online experience. The questionnaires were purposely designed for this study using Google Forms and were administered via online to the selected sample of participants (n = 12). Within the aim to obtain relevant psychographic and online behavioral data about the participants, the questionnaires were divided in three main sections: Demographics, Online Shopping, and AI Components. The complete and detailed version of the questionnaire can be found in Appendix II.

- a) Demographics: standard questions regarding gender, age, and address location were provided to characterize the sample;
- b) Online Shopping: closed-ended questions about frequency of online fashion shopping and most used devices were followed by open-ended questions on most used fashion brands and the reasons for those choices. This part was to disclose a picture of shopping habits and visualize the participants proximity (or not) with online fashion. This part ended with a dichotomous question about possible used AI components/tools, which would filter the continuation to the next section;
- c) AI Components: open- and closed-ended questions to evaluate the participants' comprehension on these tools.

Then, a participant observation based on netnography research was conducted, with a script of online shopping tasks provided to the same participant sample as of the questionnaires. The tasks were designed to recreate an online buying process through previously selected mobile apps and websites from two fashion brands. The selection of these e-commerce fashion platforms went through a lengthy process of experimentation,

based on the criteria of choosing brands that were more accessible to young consumers (price and popularity), and with enhanced UX AI in both mobile apps and desktop formats. Several trials were made with the brands Farfetch, ASOS, Levi's, Adidas, Bershka, Pull&Bear, Shein, Nike, Zara, Mango, Stradivarius, Adidas and La Redoute, in no particular order. In the end, Massimo Dutti and H&M were the most relevant across the criteria.

The participants had to execute the tasks while using the following AI tools:

- a) Voice Search: a type of technology within NLP that allows users to search for items online using voice prompts. The speech recognition system can identify the words or sentences through the microphone and convert them into a format that the machine is capable of reading, while the NLP contextualizes this new data. Only mobile apps have this tool available in their interface (Figure 9).

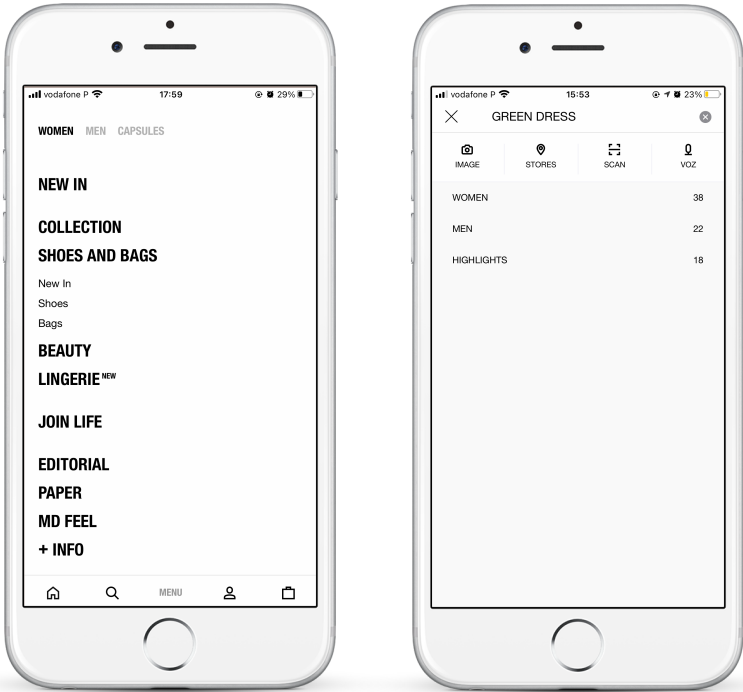


Figure 9. Voice Search on the Massimo Dutti app.

- b) Visual Search: this image recognition tool integrates CV software and enables consumers to use real-world images, such as photographs, Internet images, and

even screenshots, into their online search. The visual information (the submitted image) is processed and analyzed to create a digital object with machine-readable characteristics. From then on, a correct contextualized interpretation of the image is made, which allows the software to look for other images with similar characteristics. Most online apps from fashion retailers now provide this tool and, in this case, H&M is one of them (Figure 10).

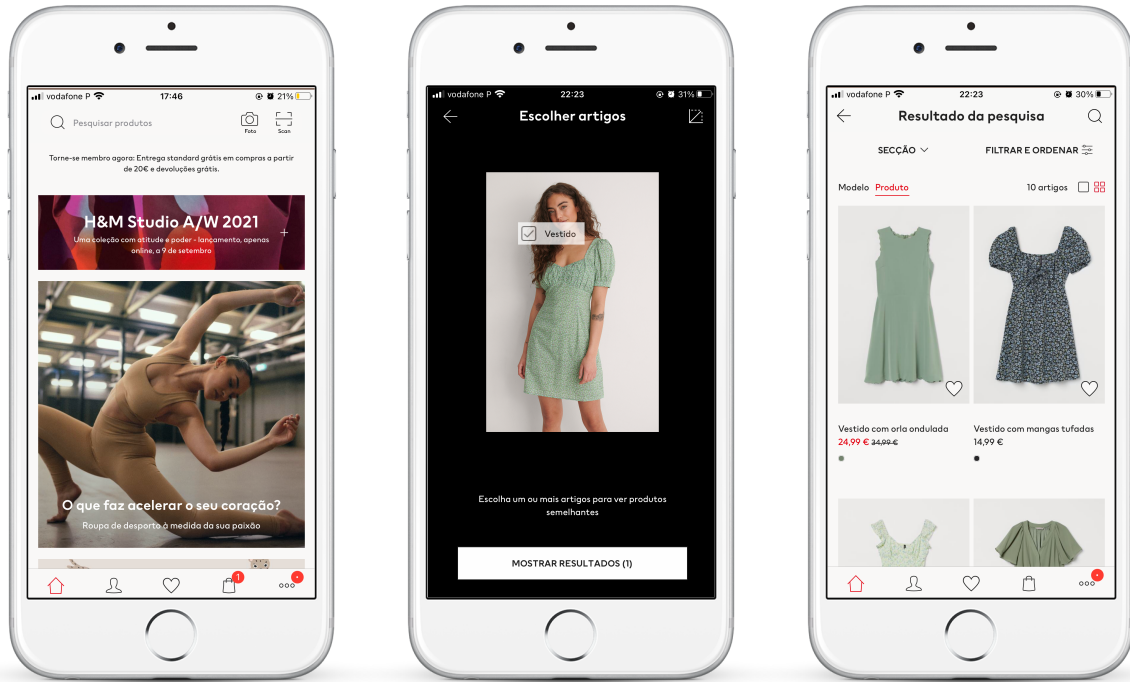


Figure 10. Visual Search on the H&M app.

- c) Recommender Systems: an algorithm designed to suggest relevant items to users, based on several factors (their preferences, for example). Circulating through data mining and machine learning, this tool is part of a predictive analytics system that filters and uncovers the most important information, dealing with a large amount of information based on the data (detected patterns) provided by users. These are mostly found on e-commerce platforms (Figure 11).

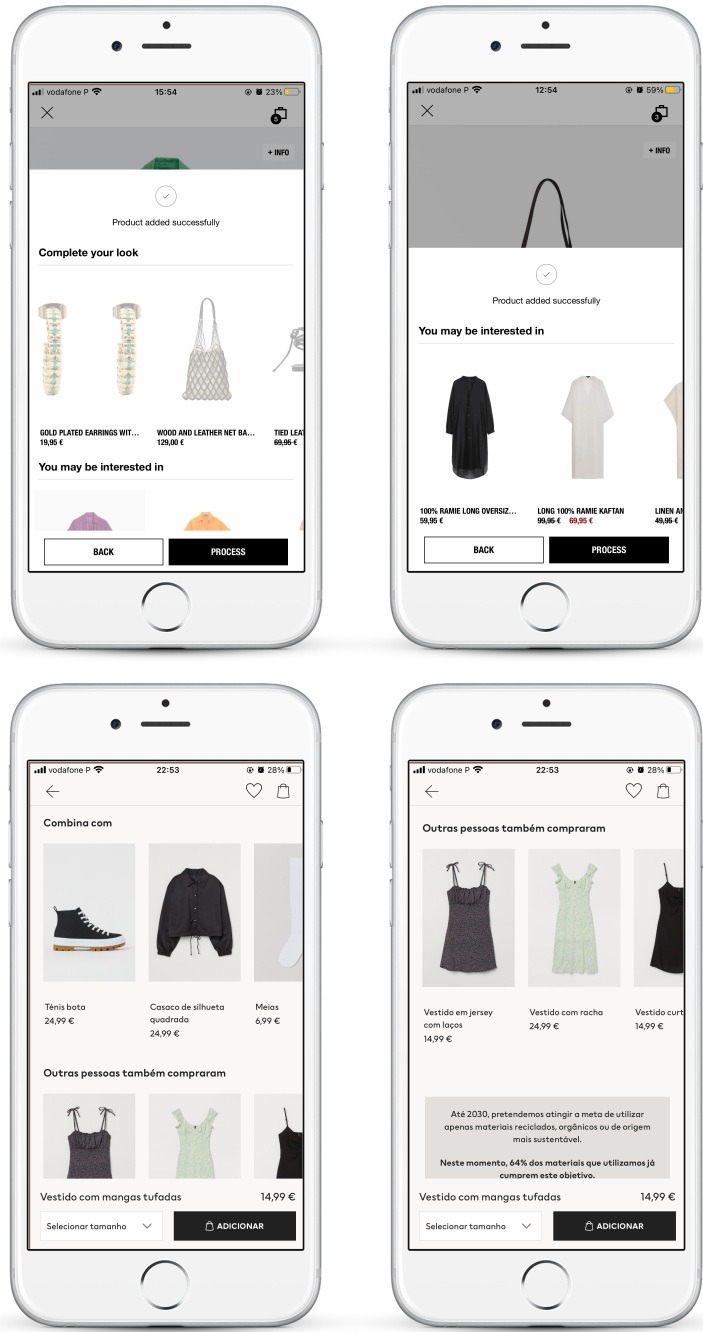


Figure 11. Recommender Systems on the Massimo Dutti and H&M apps.

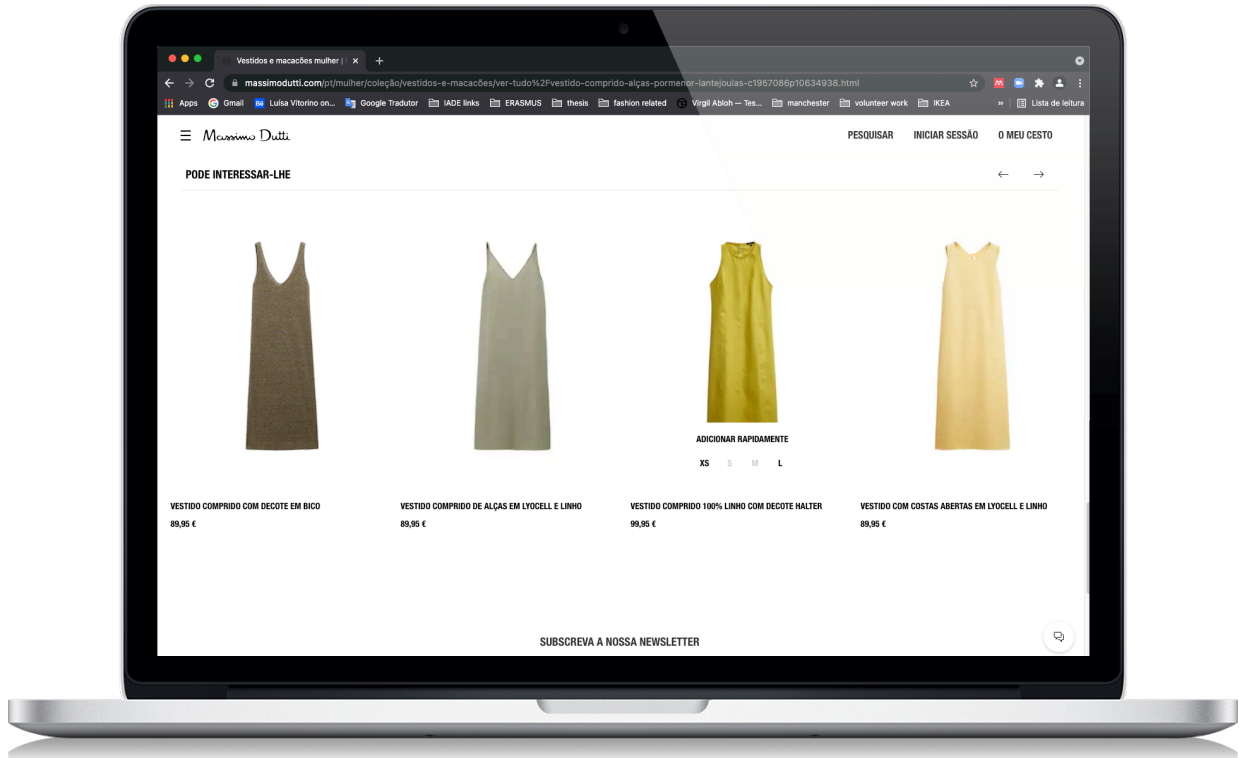
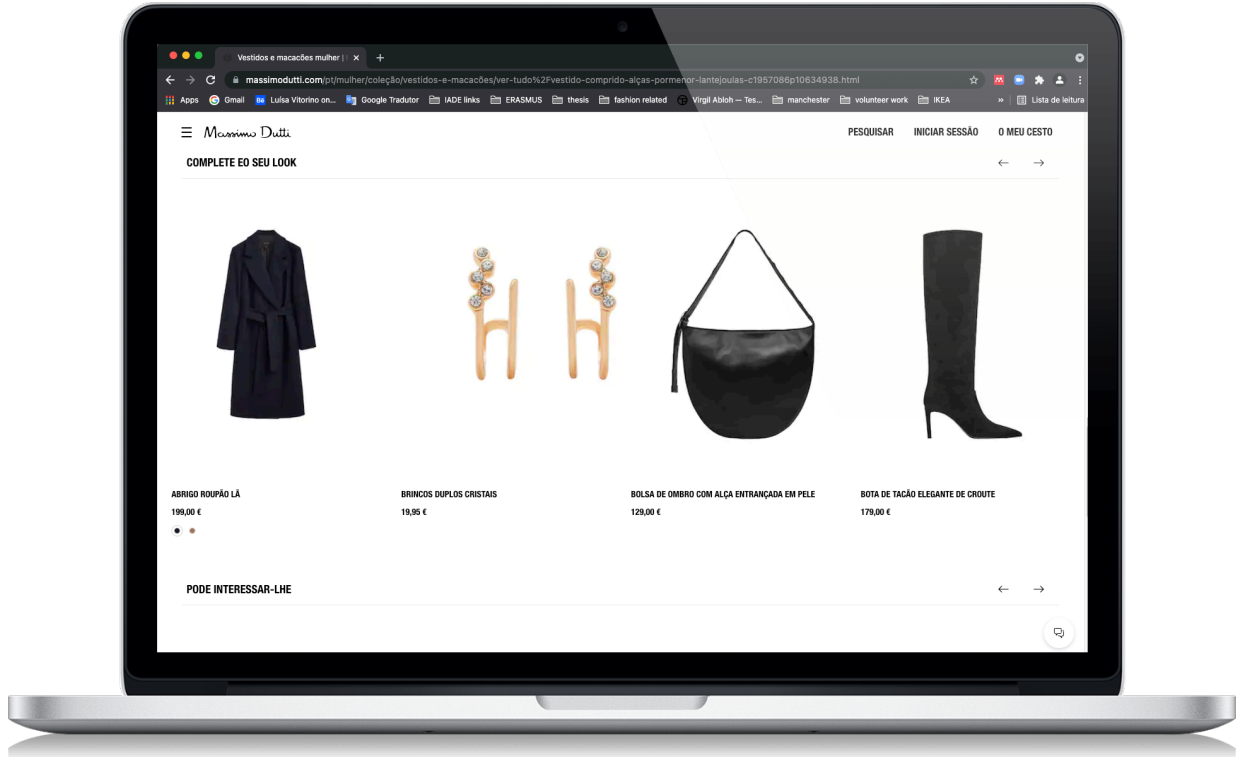


Figure 12. Recommender Systems on the Massimo Dutti website.

- d) Chatbots: NLP software applications built to simulate a human-like conversation with users and engage with automated messages. This type of software takes unstructured data, such as pieces of digital information, and makes dialog predictions after a process of comprehension and contextualization. These question answering systems can be found in standalone apps or web-based platforms, such as the example on Figure 13.

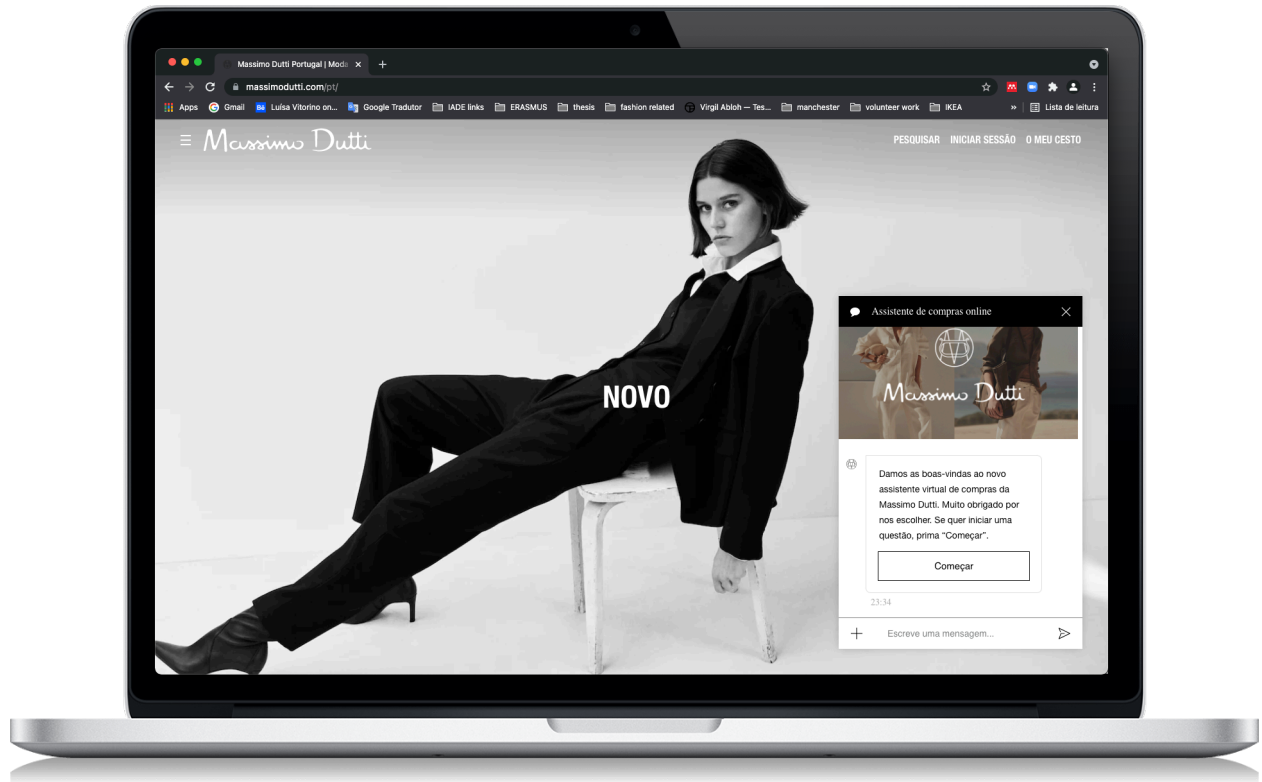


Figure 13. Chatbot on the Massimo Dutti website.

- e) Learning Fit: like other machine learning techniques, this tool inserts in a predictive analytic system which wields an algorithm capable of uncovering useful data. It is a type of data-driven personalization software that maps the size and fit from garments and footwear to users (Figure 14).

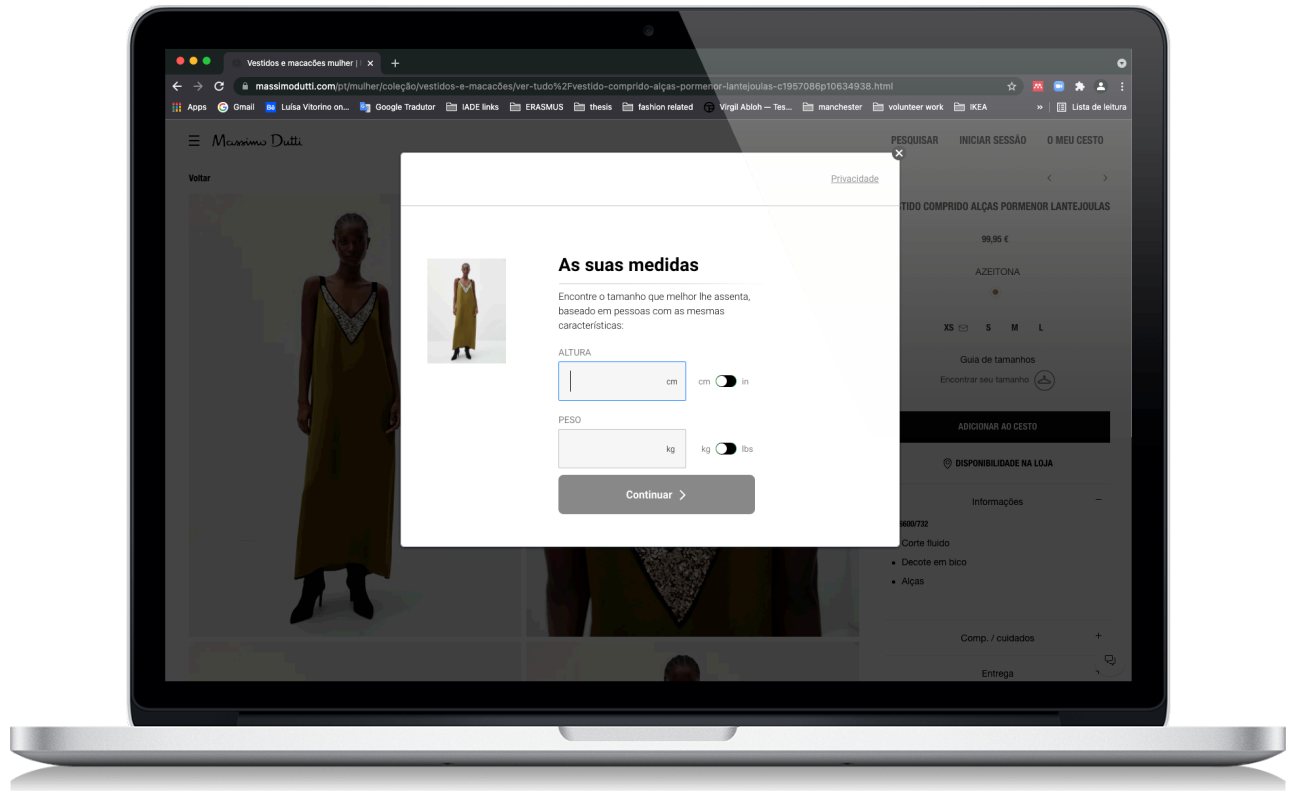


Figure 14. Learning Fit tool on the Massimo Dutti website.

- f) 3D tool: using AR, this product selection tool enables users to try on footwear to create a realistic visual. This system is able to perceive the three-dimensional reality and identify its properties (like illumination and shape) through CV technology, which then generates a 3D “experience”. By pointing their mobile device’s camera at their feet, they can have access to a more immersive experience (Figure 15).

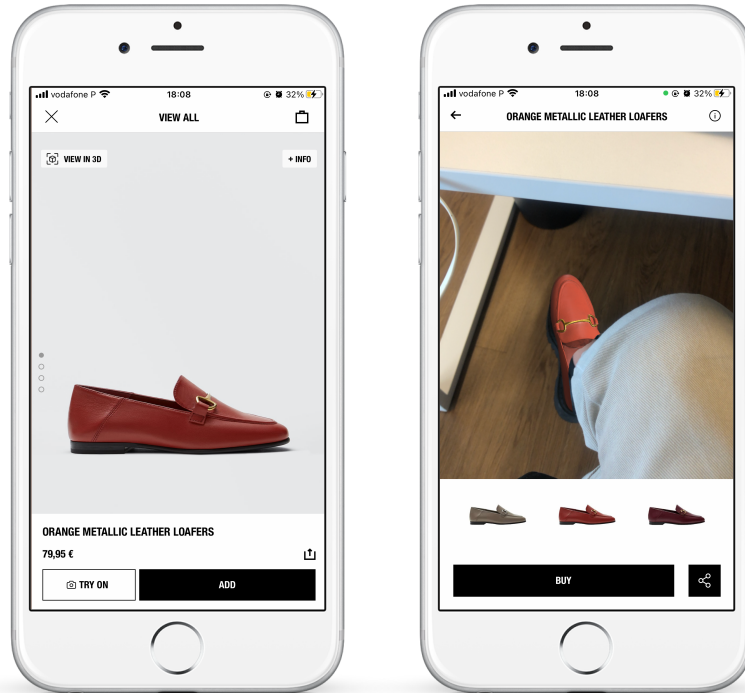


Figure 15. 3D tool on the Massimo Dutti app.

The tasks script for the observation consisted of the following configuration:

- a) 1<sup>st</sup> Scenario (using the Massimo Dutti app):
  - a. The participant had to think of one clothing item, as it would be the starting point of this scenario;
  - b. It was asked to use the voice search to find the item previously considered and choose one of preference;
  - c. After selecting the item, the participant had to run through the recommender systems and, if applicable, choose one or more items of preference.
- b) 2<sup>nd</sup> Scenario (using the Massimo Dutti website):
  - a. Considering the same clothing item as in the first scenario, the participant had to search using tools of their choice (here, the goal was to recreate an usual situation), and select one of preference;

- b. After selecting and adding the item to the cart, it was asked to use the chatbot to request assistance for a specific problem: to check availability of the item at a nearby store.
- c) 3<sup>rd</sup> Scenario (using the H&M app):
- a. The participant had to think of one fashion item (clothing, footwear, or accessories), find one picture online and save it on the mobile phone. This picture was the starting point of this scenario;
  - b. This time, it was asked to use the visual search to find the item previously considered and choose one of preference;
  - c. After selecting the item, the participant had to run through the recommender systems and, if applicable, choose one or more items of preference.
- d) 4<sup>th</sup> Scenario (using the H&M website):
- a. The participant had to think of one clothing item (it could be the same item as in the previous scenario, if it was clothing), use search tools of their choice (here, the goal was to recreate a usual situation), and select one of preference;
  - b. After choosing the item, when selecting the size, the participant had to use the learning fit to find their size.

This was the original configuration before the observations were conducted. However, right after the tests, both retailers' platforms suffered software updates which resulted in adjustments to the tasks script: the Learning Fit was initially available on the H&M website, but it was removed from the retailer's e-commerce platforms. Coincidentally, Massimo Dutti started to provide this tool whilst the observations were occurring, so it was an easy replacement. Although the 3D tool was also considered in the beginning (during the testing phase, it was available on the Massimo Dutti app), when the observations began, the tool was also removed, so it was not possible to observe its interaction.

The complete tasks script document can be found in Appendix III.

During the experiment, it was also asked to the participants to apply the *think-aloud protocol*, a method in which the participants had to “think aloud” while performing the set of tasks, whether it was related to thoughts, feelings, and actions. During this observation, the investigator assumed a participative approach, providing assistance when needed, yet not involving directly in the participants’ intentions. The observation was conducted virtually, during a video call, which was recorded with a signed consent from the participants. It was also asked the participants to share their desktop screens and record their mobile screens during the performed tasks, which were sent to the researcher afterwards. Video screen (mobile and desktop) and audio recordings were collected with the consent of the participants. As a result, a gathering of descriptive data on the observed user experience in the digital fashion platforms (mobile vs. desktop) using the AI tools was assembled.

This data then provided stimulus material for the interviews that were conducted, still in the same video call as the observation: the focus was to interpret the motives and inquire opinions and attitudes behind the participants’ behavior. The transcripts from the interviews were then assembled and ready to be interpreted according to a categorization method.

For the categorization method, the data was organized as it shows on Table 1.

	Utility	Enjoyability	Indispensability	Confidence	Accuracy	Complexity
Voice Search	Extracted from the interviews' recordings (transcripts)				Observations by the investigator (descriptive data)	
Visual Search						
Recommender systems (complementary products)						
Recommender systems (category-related)						
3D tool						
Chatbots						
Learning Fit						
<i>Others</i>						

Table 1. Categorization of the participants' insights.

The categories were chosen based on the perceptual behavior (think, feel, do) of the participants, in order to better organize and understand the insights taken from the *think-aloud protocol* and the interviews.

The interview script can be found in Appendix IV.

# Chapter IV. Data Analysis and Discussion

## 4.1. Results from the Quantitative Analysis

The sample of participants in this study was characterized by 91.7% female, and 8.3% male. The mean age was 21 years old, and their primary location was Lisbon.

In the Online Shopping section, when asked about the frequency of shopping fashion online (Figure 16), half of the respondents responded “several times a year”, which is surprising compared with the global fashion consumption tendency amongst this generation. As online consumers, the fashion shopping habits amongst this sample are less frequent, with the options: *Several times a week/Once a week/Several times a month* not being selected. However, none of the respondents replied “never” as to how frequently they shop fashion online.

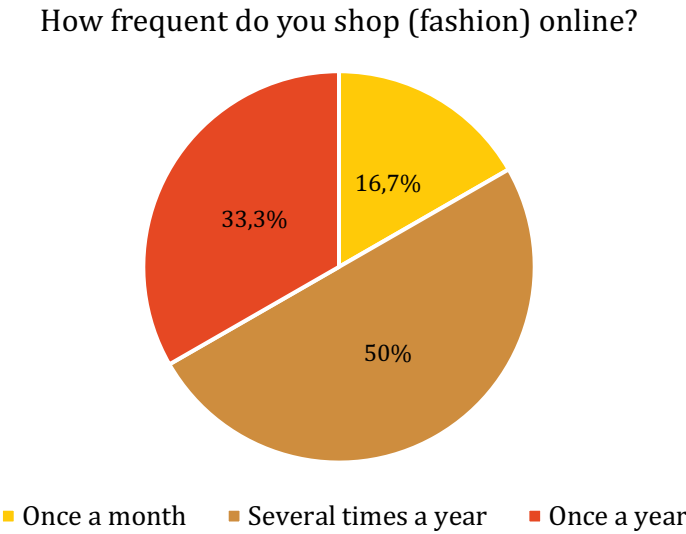


Figure 16. Frequency of shopping fashion online.

Regarding their most used devices when shopping fashion online (Figure 17), more than 80% use their computer desktop to navigate fashion e-commerce websites, whereas the remaining participants use mobile apps. Only two participants answered using both devices.

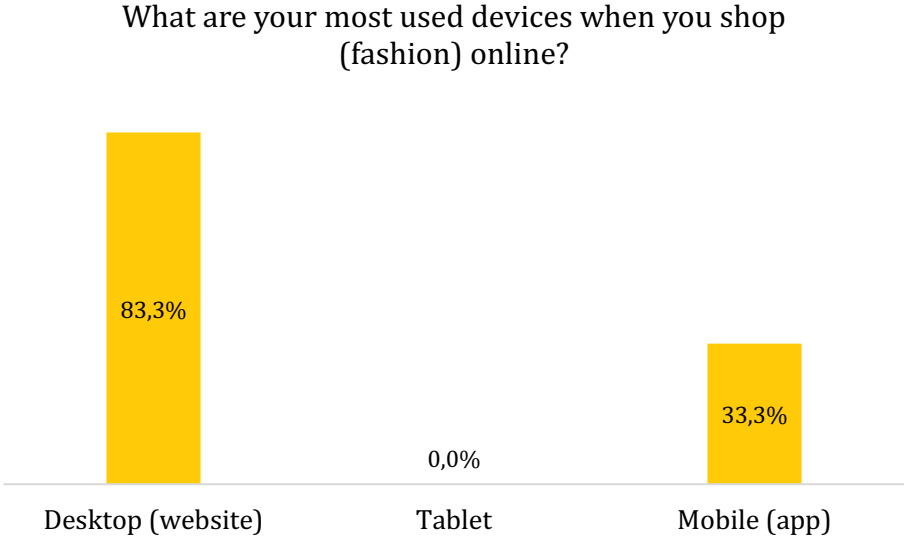


Figure 17. Most used devices when shopping fashion online.

In an open-ended question about their most frequent fashion apps/websites (Figure 18), fast fashion brands dominated the response section: Zara, H&M and Pull&Bear were the most frequent responses, followed by Stradivarius and Mango. Other mentions included Amazon, Asos and Shein, indicating the (timid) prominence of wholesale channels over DTC channels.

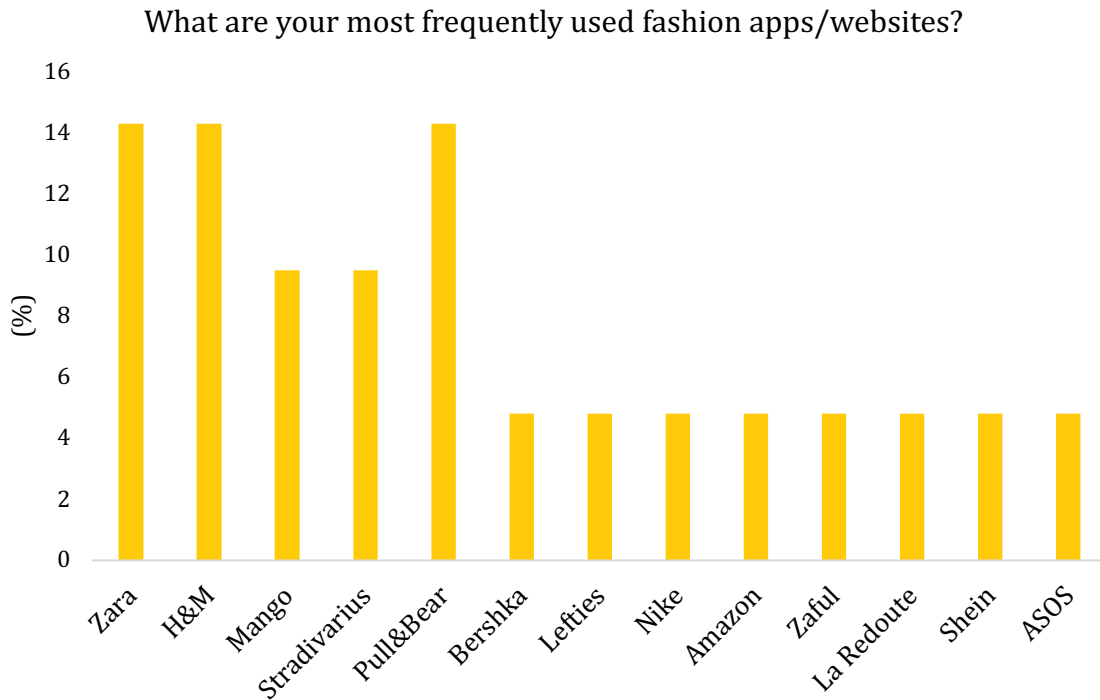


Figure 18. Most frequently used fashion platforms.

In fact, the next question about the reasons behind the use of the previously indicated brands, the main reasons behind the wholesale channels were *more variety, affordable price, and fast delivery speed*. The *style of clothes and taste preference* were the prominent responses given to justify the selection of the fast fashion brands, followed by *simple delivery and return procedures* and even *recommendation by a family member*.

About the participants' awareness of AI tools when shopping online (Figure 19), 58.3% answered they have never observed or used in e-commerce platforms, which led to the end of the questionnaire. Only 16.7% responded positively, whereas 25% are in doubt.

Have you ever observed/used an AI component(s) when shopping online? (Ex.: chatbot)

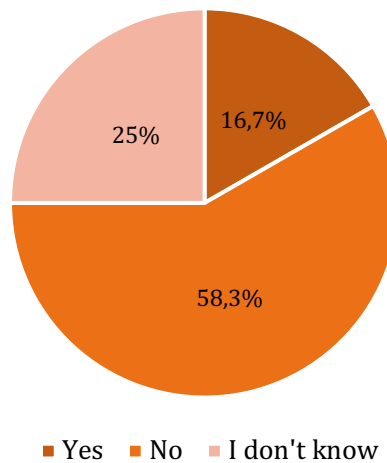


Figure 19. Observation/Usage of AI tools when shopping online.

This last question crossed over to the third and last section, AI Components, starting with an open-ended question about which tools the participants that responded positively could identify, which the only answer was *chatbots*. To the participants that were in doubt in the previous question, some options were given in order to boost their memory and help them recognize the tools (Figure 20). The response options given were: *Chatbots, Recommendation Systems, Visual/Voice Search, Smart Mirrors, Virtual Reality/Augmented Reality*, and a “I don’t know” option. Surely, despite 66.7% responding to *chatbots*, the following answer given was *visual/voice search*.

If your answer was "I don't know", do you recognize any of the following AI component(s)? (Select one option)

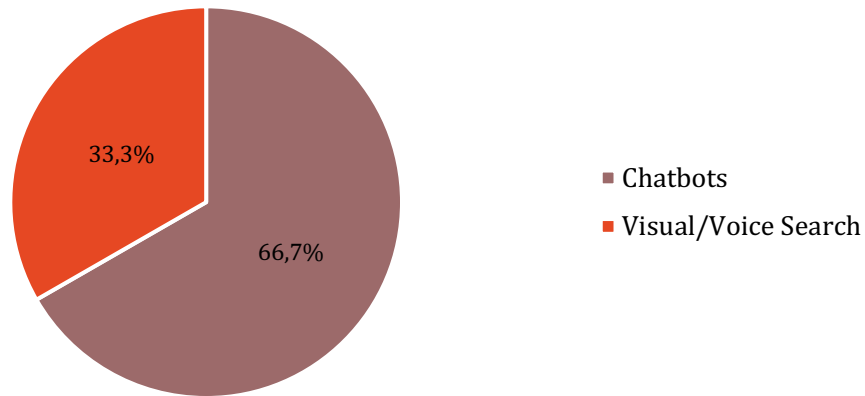


Figure 20. Recognition of AI tools.

On evaluating the usability of AI tools previously mentioned (Figure 21), most of the participants chose *neutral* to describe their opinion. The remaining responses were fairly distributed between *not useful*, *a little useful* and *useful*. None of the participants view AI tools as very useful to the e-commerce experience.

On a scale of 1 (Not Useful) to 5 (Very Useful), which option do you consider the best to describe the AI component(s) mentioned before?

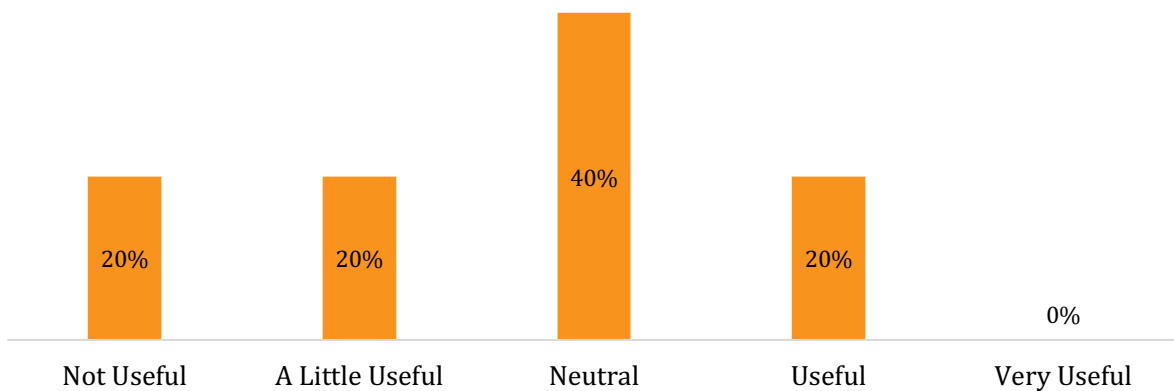


Figure 21. Usability of AI tools in e-commerce platforms.

Overall, the online shopping experience with fashion e-commerce is not very representative within this sample so it is not surprising how the interaction with AI tools fell short in the results. Perhaps the fact that more than 80% of the participants use websites to shop online also help to explain this user indifference since most of the AI tools on this type of devices relate to backoffice, like machine learning or data mining processes (except chatbots which relate to a more mainstream AI applicability of personal customer service). But the devices consumers use in this matter is irrelevant: the amount of data that is traceable and processed on the Internet is enough to identify patterns, and to discover and define trends of behavior. So even if the perceived interaction with AI tools was not conveyed in the participants' responses, it does not mean it is inexistent.

As part of the current shifting in the reality of consumption, the contingency measures consumers adopted may also explain the lower frequency of shopping. While fashion retailers are still experiencing a continuous volatility in supply and demand, consumers are still adapting from the consequences of rearranging their priorities and expectations, which dropped fashion shopping habits for last. As the "New Normal" reality settles deeper, the rational approach of the decision-making process becomes more pronounced, as consumers take more time to collect and process information to make the best decision.

## **4.2. Results from the Qualitative Analysis**

The descriptive data of the observation and the transcripts from the interviews were assembled and organized into six categories: *Accuracy, Complexity, Utility, Enjoyability, Indispensability and Confidence*. The interaction with each AI tool was analyzed according to each one of these categories:

#### **4.2.1. Voice Search**

Most of the participants were not surprised with this tool. Although it was very easy to use (one participant described it as “very basic”), the speech recognition failed for the 50% of the participants, as in terms not identified or unrelated results to the spoken input (even though the participants spoke in the language which the app was configured to assure the accuracy of the task), which eventually contributed to discredit its practicality. Besides being viewed as “useless” by most of the participants, 25% still liked the experience and even found it “funny, although it didn’t work at first”. This comes to prove that despite this type of technology does not deliver to perfection the meaning or the context of the voice inputs, it can still provide a pleasant experience and users still view the potential in this tool. Ultimately, around 40% claimed the effort of using the voice search was not worth it when compared to writing for search. However, none of the participants had physical impairments or any handicap, so in a scenario where the voice search is the only alternative, it is interesting to observe how the automation process within speech recognition is no longer sufficient in these cases and great computational linguistics developments are still needed to offset this human-machine interaction.

#### **4.2.2. Visual Search**

The interaction with this tool brought the participants to a positive consensus. Nearly 92% experienced successful results, so its usability was mainly very well perceived, while being characterized as “super useful” and a “more rapid search, because it shows immediately and almost exactly what I’m looking for”. Regarding its enjoyability, there were not any dissatisfactions amongst all the participants and, besides being completely unaware of its existence, 58.3% confidently claimed they would start using this tool more often. The reason being it has become customary for most of them to capture/save images of fashion items they enjoy, want to buy later or even to find a cheaper option somewhere else, so this tool is definitely relevant for the information search stage (one participant even described this tool as “very important” for their shopping experience). Although these types of tools,

related to computer vision, are still in a very early implementation phase, one can already behold its promising use.

### **4.2.3. Recommender Systems**

Within the tested recommender systems, there were two distinguishable models: recommendations based on complementary products (to create “a full outfit”), and recommendations centered on category-related items. For each one, the insights were slightly different. One important aspect worth mentioning is that 25% of the participants are frequent shoppers of H&M, which for the predictive analytics behind these systems, determines a different type of recommendation since it uses historical data instead of new data. Nevertheless, the results did not seem to be significantly influenced. Also, despite Massimo Dutti and H&M being two different brands (fashion style and prices), both recommender systems seemed to have impacted similarly the user experience.

In the recommendation model based on complementary products, the opinions differed between the participants. More than 40% described this recommendation as “workable, because most of the items were very appealing to me” and “a fulfilling and useful tool” that “makes sense because it completes the outfit”. To these participants, this tool is also “very persuasive” because they “always end up liking something and picking it”. Regardless, only 25% evidently assumed they liked to use this tool. On the opposite side, regarding the items suggested, 16.7% described the selection as being “too basic” and “normally, it is not something that I lean towards”. One participant interestingly reckons “these recommendations seem riskier”. Despite the ambivalence, this recommender system was able to deliver items that 58.3% of the participants enjoyed and added to cart.

The category-related recommender system was more in favor of the participants’ shopping experience, since only 16.7% think this type of recommendations “does not add anything new” as “the items are too similar”. For 75% of the participants, however, there is always some sort of interaction with this tool, whether it “facilitates immensely” when indecisive about their choice or, in a curious manner, “to make sure if I’m making the right

choice". In consonance, most of the participants expressed how they enjoy its usability. Additionally, one participant described these suggestions as a "safer choice". Further, some of these participants even admitted using this tool very regularly "especially when I'm not looking for anything in specific", but also, when looking for a specific item, "I always click on the recommendations". Overall, items suggested in this recommender system were added to 66.7% of the participants' carts.

#### **4.2.4. Chatbots**

The most contentious tool of this study was, without a doubt, the chatbot. For this study, it was considered the chatbot from Massimo Dutti, and although most of the issues participants had were related to its own interface configuration, it was possible to obtain considerable insights about its impact on the shopping experience.

During the observation, only 16.7% of the participants were able to solve their task and find a plausible answer using this chatbot. But, despite this unpleasant interaction ("it's very reductive"; "it was not useful at all"; "it was like talking to a wall"; "didn't like it at all"; "it's terrible, does not give that many response options"; "it was annoying"; "it was so confusing"), a surprising 25% still find potential in this tool, even being capable of finding "practical and agile" and insisting "if it was an item that I really wanted". Ultimately, more than 75% of the participants do not find this tool indispensable when needing assistance or it is considered as a last resort while shopping online because "there's always other ways to find the answer" they need. In reality, a very common mindset among this group of young consumers is to prefer human interaction (live chats were mentioned as a better alternative, even calling the store), unless they need immediate assistance.

Specifically with the chatbot analyzed in this study, a series of response actions in a decision tree format were given to the user, so from the participants' perspective, on one hand "it was good because it directs the search, but if you have a more specific question it won't answer" but on the other hand, "it should be able to answer only to what I wanted to know, instead of waiting for it to ask". Such a type of decision tree format has flaws when the

question answering system has too many branches, which can lead to weariness and confusion.

#### **4.2.5. Learning Fit**

In contrast with the chatbot, the learning fit was among the most acclaimed during this study. Nearly 75% of the participants found this tool to be a “great option”, “very useful”, “interesting”, “practical and credible”, indeed adding a noteworthy comment: “I love this tool, it saves me a lot of work and if a brand does not have it, I get kind of upset”. Unfamiliar with this tool were merely 16.7% of the participants, but half of this percentage claimed they would use this tool from then on, without any difficulty (despite some insights regarding that if the customer has to input too much information, it could wear them out easier). About the indispensability, almost 60% of the participants affirmed with the learning fit, they would buy online more frequently and were more confident in doing so (one participant even shared how it was frequent to order two, or even three sizes of the same item to try at home, and with this tool, that would not be no longer necessary). One insight worth taking in consideration was regarding concerns about self-esteem and how for consumers more insecure about their physical features, the fact this tool presents intimate questions (about weight and stomach/hip shape, for example), could aggravate self-awareness but also compromise the shopping experience.

Whereas the recommender systems mostly deal with new data, the predictive analytics within the learning fit encompasses historical data, which a predictive algorithm carried by a machine learning technique uses statistics to bring resulting data. The prediction system for itself (“because other customers with similar body sizes bought this, this is your size”), is not enough for customers to rely on their shopping certainties and gain confidence; here, only after the first shopping orders with this tool turn out successful customers will be able to abide with this tool and change their online shopping frequency.

#### **4.2.6. Other Considerations**

Although it was not possible to test the 3D tool, it felt pertinent to this study to collect insights about this tool during the observation and the interviews (since it was available on Massimo Dutti app before the beginning of this study), even though the interaction during the shopping experience was the primary criterion when selecting the AI tools.

When asked about how helpful this tool would be for their shopping experience, nearly 67% of the participants revealed they would start buying online more frequently if this, as it would “fill in the gap between buying online and going to the store and even “to take more risks in buying more items at one go”. However, a more skeptical approach was also identified for the rest of the participants, defending that the physical experience at the store was irreplaceable since the chance of “feeling dressed, feeling on the skin, the color” was an experience that an augmented reality tool could never reach. Nevertheless, almost 90% of these shoppers shared the sentiment that for the visualization of the item (the ability to check on angles, shapes, and several formats through augmented reality), this tool is undeniably useful and could give “more confidence about the decision process” at least.

This comes to show that even though these insights were taken from a hypothetical scenario, one can realize its full potential for the consideration stage and the decision-making process during a shopping experience. Further, as technological developments in computer vision are being accomplished and cameras become more precise and cheaper, the pursuit for better contextualized interpretation and quality images has been following its path, one that certainly most young consumers are eager to see.

## **Chapter V. Overall Conclusions, Limitations and Future Developments**

The main objective of this investigation was to comprehend how these technological techniques in AI have been affecting the consumer experience on e-commerce fashion platforms, particularly in the decision-making process.

This study approached the scope of AI and offered a contextual framework related to the user/consumer experience, then narrowing its course to the fashion industry. Although most AI applicability can be found in the “backstage” of most systems and value chains, the tools and techniques consisted of “touchpoints” are still as relevant for the research literature regarding this topic.

The online consumption is a close reality for most consumers nowadays, particularly teenagers and young adults. The impact of social media communities, influencer marketing and user-generated content has intertwined so deeply in this reality that became undeniable its impact on driving trends and pushing consumers to online consumption and their eagerness to see more and buy clever. And where does AI insert itself in this scenario? A personalized, filtered, and agile online experience can only be obtained thanks to the interaction with AI tools, and this experience seems to be exactly what these young consumers aim for. This interaction may not directly influence the intention of buying more frequently, as it was shown during this study, but it certainly impacts the decision-making process.

Moreover, the spectrum of experiences regarding these tools was quite diverse. Even though more than half of the participants in this study were not aware of the existence of most of the AI tools used, most of them had somehow already engaged with them in their previous online shopping experiences without realizing it. But when asked about it, the participants could not remember for themselves which would have reinforced the case that the interaction with AI was too superfluous for the purpose of this research. However, the qualitative approach afterwards provided a rather fruitful proposal than what it seemed at

first glance. Nonetheless, from the quantitative approach, one can assume that these young consumers do not buy fashion online more frequent (apart from personal and monetary reasons), due to the fact they commonly use websites to shop online over mobile apps, whence the interaction with AI tools is much more limited and does not bring any magnetism to the user experience.

Later, it was proved that during the online shopping environment, each AI tool affected different stages of the decision-making process, as well as also making it much more practical, quicker, and enjoyable, even without realizing it. Even in cases where the outcome from using an AI tool fell short of the expectations (for example, the voice search or the chatbot), participants were still able to visualize the potential and how those tools could be useful with different inputs or in other contexts. A failed task did not mean exactly an unpleasant one.

The visual search, on the other hand, was a tremendous successful amongst these young consumers, and it is not difficult to pinpoint the reason why. With the rise of fast fashion trends and social media, it is easy for this target to have access to thousands of visual references through their phones, scrolling between endless possibilities of style, aesthetics, and inspirations. So, combining this unlimited source of references with a tool that shortens the *when* and improves the *how* can only make the information search stage on their decision-making process more pleasant and practical. While the only limitations dwell on the fashion retailers' stock and their style offer (a failed experience using the visual search does not imply the tool was ineffective), the visual search still supports the evident success of visual personalized experiences and the importance of CV-related tools for the young customer, such as AR technology on e-commerce platforms.

With a moodboard so vast of inspirations and aesthetics, it is no wonder they became their own curators of style. Guided by influencers on social media and algorithms on e-commerce platforms, this tendency can also explain the preference of category-related recommender systems rather than complementary products to complete the outfit. These young curators are less dependent on suggestions by third parties (what looks good vs. what does not), and when it comes to evaluate their alternatives before purchasing, they prefer to

confirm whether they are making the right choice about the color, model and style of the item they previously considered. Combined with their personal taste, what's also popular and trendy amongst peers also attracts consumer's attention which reinforces the importance of social learning, in this case observational, in the consideration stage of the decision-making process.

By pushing further into AI-powered personalization service, it is (almost) possible to recreate the immersive experience physical stores can provide. However, omnichannel strategies nowadays are valuable assets for fashion brands and retailers since the combined integration of the online and offline strategy is the star ingredient of the not-so-secret recipe to gain lifetime customers. Full transparency, no digital innovation can substitute entirely the desire and necessity to look, feel and touch the products. But personalized fitting tools able to boost the customer's confidence about what size to choose and to illustrate "try on" products may have the last word on purchasing decisions on e-commerce platforms.

It should be pointed out that the conclusions from this study are preliminary, meaning that more studies with more participants towards this research topic are needed. The sample size was too unrepresentative from the generational reality and the selected participants do not fully represent the diversity of the online shopping public. Other limitations in this study came from the observation experiment and the incompatibility with a real buying environment for the participants. By asking the participants to not have in consideration values like prices and discounts while realizing their tasks, it automatically detached the online experience from the reality, since most of the buying behavior is conditioned by products' affordability. Another issue regarding this depiction conflict was the selection of the e-commerce platforms for this study, particularly with Massimo Dutti. Most participants in this study were not customers of the brand, neither it was aesthetically relatable or price attainable for them, which ultimately could have led to biased responses and decisions.

Finally, for future developments, maybe the integration and analysis of the post-purchase and advocate stages of the decision-making process could be interesting approaches to study in the impact of AI. In this sense, broadening the scope of digital platforms to social media channels, or even how multichannel experiences dwell on the rear stages of the consumer

buying behavior can serve other insightful conclusions. AI tools that were mentioned in the theoretical framework but could not be considered in the methodology, such as virtual mirrors, social shopping, and VR (all direct touchpoints to the final consumer) are part of digitally enhanced omnichannel strategies that ambitious retailers are tackling further. At the end of the day, each brand's retail strategy will invest in the intertwined universe of virtual and physical (if they are not doing it already, it is because there is a lack of resources) and the marketing and business approach will no longer escape the acceleration of e-commerce every industry is facing now, particularly in a post-pandemic reality.

## References

- Abnett, K. (2016, April 7). Is Fashion ready for the AI Revolution? *Business of Fashion*.  
<https://www.businessoffashion.com/articles/technology/is-fashion-ready-for-the-ai-revolution>
- Amed, I., Berg, A., Balchandani, A., Hedrich, S., Rölkens, F., Young, R., Jensen, J. E. (2020). *The State of Fashion 2020: Coronavirus Update*. In *The Business of Fashion and McKinsey & Company*.
- Amed, I., Berg, A., Brantberg, L., & Hedrich, S. (2020). *The State of Fashion 2021*. In *The Business of Fashion and McKinsey & Company*.
- Batkoska, L., & Koseska, E. (2012). The Impact of Cognitive Learning on Consumer Behaviour. *Procedia - Social and Behavioral Sciences*, 44, 70–77.  
<https://doi.org/10.1016/j.sbspro.2012.05.006>
- Beckwith, C. (2019, February 27). Op-Ed | Can Artificial Intelligence Ever Understand Fashion?. *Business of Fashion*. <https://www.businessoffashion.com/opinions/news-analysis/op-ed-can-artificial-intelligence-ever-understand-fashion>
- Beheshti-Kashi, S., Karimi, H. R., Thoben, K. D., Lütjen, M., & Teucke, M. (2015). A survey on retail sales forecasting and prediction in fashion markets. *Systems Science and Control Engineering*, 3(1), 154–161. Taylor and Francis Ltd.  
<https://doi.org/10.1080/21642583.2014.999389>
- Blázquez, M. (2014). Fashion shopping in multichannel retail: The role of technology in enhancing the customer experience. *International Journal of Electronic Commerce*, 18(4), 97–116. <https://doi.org/10.2753/JEC1086-4415180404>
- Bonera, M., & Corvi, E. (2012). The online buying process in the fashion industry. *10th International Marketing Trends Conference*, 53(9), 1–20.

- Boos, C. (2018, April 27). How Fashion Should (and Shouldn't) Embrace Artificial Intelligence. *Business of Fashion*.  
<https://www.businessoffashion.com/opinions/news-analysis/how-fashion-should-and-shouldnt-embrace-artificial-intelligence>
- Briedis, H., Kronschnabl, A., Rodriguez, A., & Ungerman, K. (2020, May). Adapting to the next normal in retail: The customer experience imperative. *McKinsey & Company*.  
<https://www.mckinsey.com/industries/retail/our-insights/adapting-to-the-next-normal-in-retail-the-customer-experience-imperative>
- Brownlee, J. (2019, June 17). A Gentle Introduction to Generative Adversarial Networks (GANs). *Machine Learning Mastery*. <https://machinelearningmastery.com/what-are-generative-adversarial-networks-gans/>
- Cao, P., Meister, S., & Klante, O. (2014). How Social Media Influence Apparel Purchasing Behavior. *Marketing Review St. Gallen*, 31(6), 77–86. <https://doi.org/10.1365/s11621-014-0427-y>
- Cetină, I., Munthiu, M.-C., & Rădulescu, V. (2012). Psychological and Social Factors that Influence Online Consumer Behavior. *Procedia - Social and Behavioral Sciences*, 62, 184–188. <https://doi.org/10.1016/j.sbspro.2012.09.029>
- Chilet, J. A., Chen, C., & Lin, Y. (2016). Analyzing social media marketing in the high-end fashion industry using Named Entity Recognition. *Proceedings of the 2016 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM)*, pp. 621–622. <https://doi.org/10.1109/ASONAM.2016.7752300>
- Choi, T.-M., Hui, C.-L., Yu, Y. (2011). Intelligent time series fast forecasting for fashion sales: A research agenda. *Institute of Textiles and Clothing, The Hong Kong Polytechnic University*, pp. 1010-1014. <https://doi.org/10.1109/ICMLC.2011.6016870>
- Choi, T.-M. (2012). *Fashion Supply Chain Management: Industry and Business Analysis*. Business Science Reference, IGI Global.

- Choi, T.-M. (2014). *Fashion Branding and Consumer Behaviors*. Springer.  
[https://doi.org/10.1007/978-1-4939-0277-4\\_6](https://doi.org/10.1007/978-1-4939-0277-4_6)
- Cooke, L. (2010). Assessing concurrent think-aloud protocol as a usability test method: A technical communication approach. *IEEE Transactions on Professional Communication*, 53(3), 202–215. <https://doi.org/10.1109/TPC.2010.2052859>
- Costello, L., McDermott, M.-L., & Wallace, R. (2017). Netnography: Range of Practices, Misperceptions, and Missed Opportunities. *International Journal of Qualitative Methods*, 16(1), 1–12. <https://doi.org/10.1177/1609406917700647>
- Creswell, J. W., & Creswell, J. D. (2018). *Research Design: Qualitative, Quantitative and Mixed Methods Approaches*. Sage Pub. Inc.
- Del Rey, J. (2017, March 1). One of Facebook Messenger's first retail partners has ditched it as a notification tool. *Vox*. <https://www.vox.com/2017/3/1/14779978/everlane-facebook-messenger-stop-customer-service-notifications>
- Denscombe, M. (2012). *Research Proposals - A practical guide*. McGraw-Hill.
- Dey, S. (2019, March 27). What is the Difference Between: Data Science, Data Mining and Machine Learning. *Dimensionless*. <https://dimensionless.in/what-is-the-difference-between-data-science-data-mining-and-machine-learning/>
- Drapers. (2020). *Gen Z and Millennials 2020*. In EMAP Publishing Company.  
<https://www.drapersonline.com/guides/gen-z-and-millennials-2020>
- Eisenstein, J. (2019). *Introduction to Natural Language Processing*. The Massachusetts Institute of Technology.
- EL Boukkouri, H. (2018, June 18). Text Classification: The First Step Toward NLP Mastery. *Medium*. <https://medium.com/data-from-the-trenches/text-classification-the-first-step-toward-nlp-mastery-f5f95d525d73>

- Eliot, L. (2018, January 2). Expert Systems and AI Self-Driving Cars: Crucial Innovative Techniques. *AI Trends - The Business and Technology of Enterprise AI*. <https://www.aitrends.com/ai-insider/expert-systems-ai-self-driving-cars-crucial-innovative-techniques/>
- Fernandez, C. (2021, February 3). DTC vs Wholesale: Striking the Right Balance. *Business of Fashion*. <https://www.businessoffashion.com/articles/retail/dtc-vs-wholesale-the-great-debate-continues>
- Giri, C., Jain, S., Zeng, X., & Bruniaux, P. (2019). *A Detailed Review of Artificial Intelligence Applied in the Fashion and Apparel Industry*. IEEE Access. <https://doi.org/10.1109/ACCESS.2019.2928979>
- Guercini, S., Bernal, P. M., & Prentice, C. (2018). New marketing in fashion e-commerce. *Journal of Global Fashion Marketing*, 9(1), 1–8. <https://doi.org/10.1080/20932685.2018.1407018>
- Hendler, J., Tate, A., & Drummond, M. (1990). AI Planning - Systems and techniques. *AI Magazine*, 11(2), 61–77.
- Hennessy, M. (2021, January 25). Makers of Sophia the robot plan mass rollout amid pandemic. *Reuters*. <https://www.reuters.com/article/us-hongkong-robot-idUSKBN29U03X>
- Hui, P. C., Chan, K. C. C., Yeung, K. W., & Ng, F. S. (2007, October). Application of artificial neural networks to the prediction of sewing performance of fabrics. *International Journal of Clothing Science and Technology*, 19(5), 291–318. <https://doi.org/10.1108/09556220710819500>
- Jelil, R. (2018). Textile Materials and Processes Research Unit MPTex. In Thomassey, S., & Zeng, X. (Eds.), *Artificial Intelligence for Fashion Industry in the Big Data Era*. Springer Series in Fashion Business, pp. 97-123. [https://doi.org/10.1007/978-981-13-0080-6\\_6](https://doi.org/10.1007/978-981-13-0080-6_6)

Kamath, U., Liu, J., & Whitaker, J. (2019). *Deep Learning for NLP and Speech Recognition*. Springer. <https://doi.org/10.1007/978-3-030-14596-5>

Kansara, V. A. (2013, May 3). The Long View | Big Data Will Change All Aspects of the Fashion Industry. *Business of Fashion*. <https://www.businessoffashion.com/articles/technology/the-long-view-big-data-will-change-all-aspects-of-the-fashion-industry>

Khillar, S. (2020, January 6). Difference Between Speech Recognition and Natural Language Processing. *Difference Between*. <http://www.differencebetween.net/technology/difference-between-speech-recognition-and-natural-language-processing/>

Knight, W. (2017, August 2017). Amazon Has Developed an AI Fashion Designer. *MIT Technology Review*. <https://www.technologyreview.com/2017/08/24/149518/amazon-has-developed-an-ai-fashion-designer/>

Lo, W.-S., & Hong, T.-P. (2012). A Three-Level Multiple-Agent Early Warning Mechanism for Preventing Loss of Customers in Fashion Supply Chains. In Choi, T.-M. (Eds.), *Fashion Supply Chain Management: Industry and Business Analysis*. Business Science Reference, IGI Global (pp. 173-184).

Long, D. & Fox, M. (2002, October). Progress in AI Planning Research and Applications. *UPGRADE (European Online Magazine for the Information Technology Professionals)*, 3(5).

Luce, L. (2019). *Artificial Intelligence for Fashion*. APRESS. <https://doi.org/10.1007/978-1-4842-3931-5>

Masterson, R., & Pickton, D. (2014). *Marketing: An Introduction*. SAGE Publications.

- McKinsey & Company. (2019). The State of Fashion 2019. *McKinsey & Company*.  
[https://www.mckinsey.com/~media/McKinsey/Industries/Retail/Our Insights/The State of Fashion 2019 A year of awakening/The-State-of-Fashion-2019-final.ashx](https://www.mckinsey.com/~media/McKinsey/Industries/Retail/Our%20Insights/The%20State%20of%20Fashion%202019%20A%20year%20of%20awakening/The-State-of-Fashion-2019-final.ashx)
- Meler, A., & Stormer, H. (2009). *eBusiness and eCommerce - Managing the Digital Value Chain*. Springer.
- Metaxiotis, K. S., Askounis, D. & Psarras, J. (2002). Expert systems in production planning and scheduling: A state-of-the-art survey. *Journal of Intelligent Manufacturing*, 13, pp. 253–260. <https://doi.org/10.1023/A:1016064126976>
- Mobasher, B., & Anand, S. S. (2003). *Intelligent Techniques for Web Personalization*. Springer.
- Nadkarni, P. M., Ohno-Machado, L., & Chapman, W. W. (2011). Natural language processing: An introduction. *Journal of the American Medical Informatics Association*, 18(5), 544–551. <https://doi.org/10.1136/amiajnl-2011-000464>
- Nanda, M. C., (2020). Gen-Z Shopping: Separating Myth from Reality. *Business of Fashion*.
- Pan, Z., Yu, W., Yi, X., Khan, A., Yuan, F., Zheng, Y. (2019, March 14). Recent Progress on Generative Adversarial Networks (GANs): A Survey. *IEEE Access*, 7, 36322-36333. <https://doi.org/10.1109/ACCESS.2019.2905015>
- Rath, P. M., Bay, S., Petrizzi, R., & Gill, P. (2016). *The Why of the Buy*. Fairchild Books. <https://doi.org/10.5040/9781501304293>
- Ren, S., Patrick Hui, C. & Jason Choi, T. (2018). AI-Based Fashion Sales Forecasting Methods in Big Data Era. In Thomassey, S., & Zeng, X. (Eds.), *Artificial Intelligence for Fashion Industry in the Big Data Era*. Springer Series in Fashion Business, pp. 9-26. [https://doi.org/10.1007/978-981-13-0080-6\\_15](https://doi.org/10.1007/978-981-13-0080-6_15)
- Rodrigues, E. M. & Figueiredo, M. C. (2013). Forecasting Demand in the Clothing Industry. *XI Congreso Galego de Estatística e Investigación de Operacións*.

- Rotar, A., Lasquety-Reyes, J., Suhren, L., Péter, M., Wang, S., Fischer, S., Blumtritt, C., Färber, J., Senn-Kalb, L., Lindlahr, S., Zavalova, S., & Han, Y. (2020). *Digital Economy Compass 2020*. Statista.
- SanMiguel, P., & Sádaba, T. (2018). Nice to be a fashion blogger, hard to be influential: An analysis based on personal characteristics, knowledge criteria, and social factors. *Journal of Global Fashion Marketing*, 9(1), 40–58. <https://doi.org/10.1080/20932685.2017.1399082>
- Scientific American, (2002). *Understanding Artificial Intelligence (Science Made Accessible)*. Grand Central Publishing.
- Shaw, K. (2019, December 16). The Robotics Sector in 2020 and Beyond: Predictions from Industry Gurus. *Robotics Business Review*. <https://www.roboticsbusinessreview.com/news/the-robotics-sector-in-2020-and-beyond-predictions-from-industry-gurus/>
- Sherman, L. (2020, October 28). How to Build Wholesale Relationships Without Getting Squeezed. *Business of Fashion*. <https://www.businessoffashion.com/articles/luxury/how-to-build-wholesale-relationships-without-getting-squeezed>
- Song, X., Yang, S., Huang, Z., & Huang, T. (2019). The Application of Artificial Intelligence in Electronic Commerce. *Journal of Physics: Conference Series*, 1–7. <https://doi.org/10.1088/1742-6596/1302/3/032030>
- Stephens, D. L. (2014). *Essentials of Consumer Behavior*. Routledge. <https://doi.org/10.2307/1250509>
- Stankevich, A. (2017). Explaining the Consumer Decision-Making Process: Critical Literature Review. *Journal of International Business Research and Marketing*, 2(6), 7–14. <https://doi.org/10.18775/jibrm.1849-8558.2015.26.3001>

- Szeliski, R. (2010). *Computer vision: Algorithms and Applications*. Springer.  
<https://doi.org/10.4324/9780429042522-10>
- Thomassey, S., & Zeng, X. (Eds.). (2018). *Artificial Intelligence for Fashion Industry in the Big Data Era*. Springer Series in Fashion Business, pp. 1-5. [https://doi.org/10.1007/978-981-13-0080-6\\_15](https://doi.org/10.1007/978-981-13-0080-6_15)
- Torresen, J. (2018, January 15). A Review of Future and Ethical Perspectives of Robotics and AI. *Frontiers in Robotics and AI*. <https://doi.org/10.3389/frobt.2017.00075>
- van der Aalst, W. (2016). *Process Mining – Data Science in Action* (2<sup>nd</sup> ed.). Springer.  
[https://doi.org/10.1007/978-3-662-49851-4\\_1](https://doi.org/10.1007/978-3-662-49851-4_1)
- Wang, F., Wang, M., Wan, Y., Jin, J., & Pan, Y. (2021). The power of social learning: How do observational and word-of-mouth learning influence online consumer decision processes? *Information Processing and Management*, 58(5).  
<https://doi.org/10.1016/j.ipm.2021.102632>
- Warwick, K. (2013). *Artificial intelligence: The Basics*. Routledge.  
<https://doi.org/10.4324/9780203802878>
- We Are Social. (2020). *Digital 2020 – October Global Statshot Report*. Hootsuite.
- Wilkins, D. E., (1990). *Practical Planning: Extending the Classical AI Planning Paradigm*. Morgan Kaufmann Publishers, pp. 1.
- Wong, W. K. & Chan, C. K. (2001). An Artificial Intelligence Method for Planning the Clothing Manufacturing Process. *The Journal of The Textile Institute*, 92(2), 168-178.  
<https://doi.org/10.1080/00405000108659606>
- Mueller, J. P., & Massaron, L. (2016). *Machine Learning for dummies*. John Wiley & Sons, Inc.
- Kamath, U., Liu, J., & Whitaker, J. (2019). *Deep Learning for NLP and Speech Recognition*. Springer. <https://doi.org/10.1007/978-3-030-14596-5>

Xiang, L., Zheng, X., Lee, M. K. O., & Zhao, D. (2016). Exploring consumers' impulse buying behavior on social commerce platform: The role of parasocial interaction. *International Journal of Information Management*, 36(3), 333–347. <https://doi.org/10.1016/j.ijinfomgt.2015.11.002>

Zimmermann, H.-J. (2011). *Fuzzy Set Theory – and Its Applications*. Springer Science and Business Media.

# Appendices

## Appendix I – Informed Consent

### INFORMED CONSENT

---

#### Project Title

Observational study regarding the applicability of AI components in e-commerce fashion platforms.

#### Study Framework

You have been invited to participate, as a volunteer, in an observational study, in the scope of a research work taking place at IADE - European University. Your participation represents an important contribution to the project, which its main objective is to evaluate the applicability of AI components in fashion e-commerce platforms (mobile and desktop), through the crossing of demographic and psychographic data of the participants and qualitative data (observational experiment and interview testimony).

Participation in this research is voluntary and confidential, so you may decide to stop the session and leave the study at any time without penalty. If you agree to take part in this study, you must sign this document and send it to the investigator in charge.

#### Confidentiality of data

All data collected will be uncharacterized and confidential. To this end, participants will be identified only with a number that serves for the researcher to have a record of the sequence in which the experiment took place. Video screen (mobile and desktop) and audio recordings will be used, exclusively for the purpose of this research and will not compromise the individual results of these study. No individual identities will be used in any reports or publications resulting from the study.

#### Contact

For further clarifications or questions related to this research you can contact the person in charge by e-mail – [luisa.vitorino@gmail.com](mailto:luisa.vitorino@gmail.com).

### **Consent**

By signing this document, you are stating that you have nothing to object and are therefore willing to participate in this study.

Participant Name: \_\_\_\_\_

Participant Signature: \_\_\_\_\_

Date: \_\_/\_\_/\_\_

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Responsible for the research: Luísa Vitorino | [luisa.vitorino@gmail.com](mailto:luisa.vitorino@gmail.com)

## Appendix II - Questionnaire

### Applicability of AI components in e-commerce fashion platforms

As an element of a master thesis, inserted in the IADE's Design and Advertising master program, this questionnaire is part of a study that investigates the applicability of artificial intelligence (AI) in e-commerce fashion platforms, more specifically to evaluate the interaction with AI components. The aim of this questionnaire is to collect demographic and previous online experience data about the participants.

All data collected will be uncharacterized and confidential only for the purpose of this research.

If you feel more comfortable, your answers can be written in Portuguese.

### Demographics

1. What is your gender? \*

- Feminine
- Masculine
- Non-Binary
- Other
- Rather Not Say

2. What is your age? \*

---

3. Where are you currently living? (City, Country) \*

---

## Online Shopping

4. How frequent do you shop (fashion) online? \*

- Several times a week
- Once a week
- Several times a month
- Once a month
- Several times a year
- Once a year
- Never

5. What are your most used devices when you shop (fashion) online? \*

- Desktop (website)

- Tablet (app)
- Mobile (app)
- Outra opção...

6. What are your most used devices when you shop (fashion) online? \*

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7. Explain the reason(s) why you use the indicated apps/websites. \*

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8. Have you ever observed/used an AI component(s) when shopping online? (Ex.: Chatbot)\*

- Yes
- No
- I don't know

## AI components

9. If your answer was “yes”, which one(s)?

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10. On a scale of 1 (Not Useful) to 5 (Very Useful), which option do you consider the best to describe the AI component(s) mentioned before?

1 – Not Useful | 2 – A Little Useful | 3 – Neutral | 4 – Useful | 5 – Very Useful

	1	2	3	4	5	
Not Useful	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	Very Useful

11. Would you like to add something about the AI component(s) mentioned before?

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## Appendix III - Study Script Tasks

# APPLICABILITY OF AI COMPONENTS IN E-COMMERCE FASHION PLATFORMS

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Thank you for being part of this study.

As an element of a master thesis, inserted in the IADE's Design and Advertising master program, this study investigates the applicability of artificial intelligence (AI) in e-commerce fashion platforms, more specifically to evaluate the interaction with AI components. The aim of this study is to observe if there's an impact of AI components in the customer journey within e-commerce fashion platforms.

This study comprises three parts: a brief questionnaire, an observational experiment, and a short interview.

The data that will be collected (Google Forms questionnaire) and recorded (mobile screen, video call and audio recording during the experiment and the final interview) will be handled uncharacterized and confidentially only for this research.

To start, I will ask you to fill in a brief questionnaire regarding demographics and previous online experience.

This will take 5 minutes.

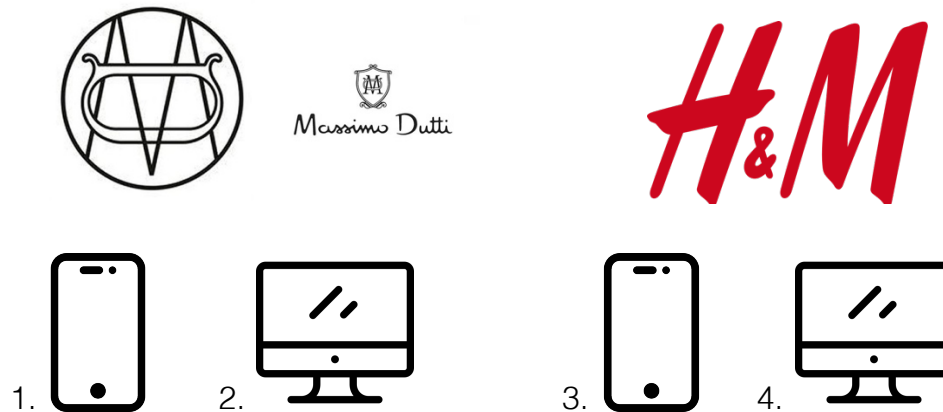
Questionnaire link: <https://forms.gle/Bn2nTF6tD99Kmhft7>

After submitting the questionnaire, please **keep the camera on** during the entire experiment.

The video recording of this experiment will start now.

## Tasks Script Guide

For this experiment, there will be four scenarios, two for each fashion brand:



Firstly, you will use the Massimo Dutti app (1<sup>st</sup> scenario), then proceed to the Massimo Dutti website on your computer (2<sup>nd</sup> scenario). Afterwards, you will have to return to your mobile phone to use the H&M app (3<sup>rd</sup> scenario), thus finishing the experiment on the desktop H&M website (4<sup>th</sup> scenario).

To make the data gathering process more effective and convincing, this experiment will use the **think-aloud protocol**: this method implies the participants to think aloud while performing the set of tasks, by saying whatever comes into mind: thoughts, feelings and even what you are doing. There is no wrong answer, so feel freely to speak.

## 1<sup>st</sup> Scenario – Reach for your mobile phone.

1. I would like to ask you to think of a **clothing** item (without relating it to a brand). **This item will be the starting point for the first scenario.**
  - a. Before beginning the following tasks, please **start recording your mobile screen.**
  - b. Open the app **Massimo Dutti**;
  - c. Use the **voice search** to describe the item you previously chose.

Note: After every search (always within the **think-aloud protocol**), **describe whether the size of your clothing item** is available.

- d. Select the item that match your search and after you choose your size, click on the option “Add”.

Note: **Only** if your size is not available, (always within the **think-aloud protocol**), **describe it to the researcher**, go back to the previous menu and select another item until you find your size.

- e. In the section “You may be interested in”, some items are suggested. Select the most preferable one(s), and after you choose your size, click on the option “Add”. If you are not satisfied with the automatic selection, you can choose to skip this task and proceed to the next one.
- f. Click on the option “Process”.
- g. **You can stop the mobile screen recording.**

## 2<sup>nd</sup> Scenario – Switch to your computer:

1. To begin this task, **within the video call**, please **start sharing your desktop screen**.
2. Imagine a problem occurred with the app. Open the browser on your computer and open the **website** <https://www.massimodutti.com/pt/>.
3. Search for the same **clothing** item as you initially did on the app. You can use other tools to do this task.
4. Choose the most preferable one(s) according to your search and after you choose your size, click on the option “Processar pedido”.

Note: If your size is not available, (always within the **think-aloud protocol**), **describe it to the researcher**, go back to the previous menu and select another item until you find your size. Add it to cart.

5. Now pretend you need assistance to check if the item you added to cart is in stock in a nearby store.
6. Click on the “Chat”, on the bottom-right corner of the window, to start a conversation. Follow the instructions given in the chatbot.

Note: If the instructions given by the chatbot are not clear or didn’t solve your question, write in the text bar “Encontrar o meu item numa loja”. / “Verificar a disponibilidade de um artigo”.

7. **Without disconnecting from the video call**, you can now **stop sharing your screen**.

## 3<sup>rd</sup> Scenario – Reach for your mobile phone again:

1. I would like to ask you to think of one **fashion item (clothing, shoes or accessory)**, **without relating to a brand**. Find **one picture** of that item (using Google, for example) and save it in your mobile device. **This picture will be the starting point for the third scenario.**
  - a. Before beginning the following tasks, please **start recording your mobile screen**.
  - b. Open the app **H&M**.
  - c. Use the **visual search** to upload the image you previously found.

Note: If the visual search was not successful, please **exit the app** and **find another picture online**. Save it on your device and use the visual search again. Proceed with the tasks.

- d. Select the item that match your search (if applicable, choose your size).

Note: After every search (always within the **think-aloud protocol**), **describe whether the size (if applicable) of your fashion item** is available.

- e. Add it to cart.

Note: If your size is not available (always within the **think-aloud protocol**), **describe it to the researcher**, go back to the previous menu and select another item until you find your size. Add it to cart.

- f. In the top-left corner, select the cart option.
- g. Scroll down the page until the section “Poderá também gostar de”, where some items are suggested.

- h. Select the most preferable one(s) (if applicable, choose your size), and add to cart. If you are not satisfied with the automatic selection, you can choose to skip this task and proceed to the next one.

Note: If your size is not available, (always within the **think-aloud protocol**), **describe it to the researcher**, go back to the previous menu and select another item until you find your size. If you are not satisfied with the automatic selection, you can choose to skip this task and proceed to the next one.

- i. **You can stop the mobile screen recording.**

#### **4<sup>th</sup> and last Scenario – Switch to your computer again:**

1. To begin this task, **within the video call**, please **start sharing your desktop screen**.
2. Open the browser on your computer and open the **website**:  
[https://www2.hm.com/pt\\_pt/index.html](https://www2.hm.com/pt_pt/index.html).
3. I would like to ask you to think of a **clothing** item (without relating it to a brand). You can use other tools to do this task.
4. When selecting the size, click on the option “Encontrar o meu tamanho” to find your size.

5. Follow the instructions. After every search (always within the **think-aloud protocol**), **describe whether the size of your clothing item** is available.
6. Add it to cart.
7. **Without disconnecting from the video call**, you can now **stop sharing your screen**.

You have now completed this experiment. Thank you for your time!

Before we move on to the next and last step of this study, please send to [luisa.vitorino@gmail.com](mailto:luisa.vitorino@gmail.com) the mobile screen recordings from your phone.

After this, a short interview will be held which will take 10 minutes.

## Appendix IV – Interview Script

### INTERVIEW SCRIPT

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#### (Experiment overall feeling/perception)

- How did the interaction with these components influenced your decision-making process?
- Are you satisfied with both of your card selections (app and website)?
- Would you buy the items in both carts?
- Was there any issue that should be taken in consideration?

#### (AI Perception)

- What did you feel about using the voice search, comparing to the visual search?
- About the recommendation systems (“Complete your look” and “You may be interested in”), how would you describe their automatic selection of the items? Did you find any difference between brands and their recommendation systems?
- What did you feel about using the fitting tool (“True Fit”)? Would you feel confident in buying the recommended size?
- How would you evaluate your experience with the chat assistance?
- Do you have any concerns regarding privacy by using any of these AI components?

#### (Final thoughts)

- Is there anything you would like to add regarding this experiment and your overall experience?

How would you describe the 3D tool for your online shopping experience?