LUISS

Dipartimento
di Impresa e Management

Cattedra Specifica: Behavioural economics and consumption theories

Building trust in robots: the interplay of customer knowledge, embarrassment, robot anxiety and robot design on trust in service robots

Prof. Giacomo Sillari
RELATORE

Prof. Giovanni Ponti
CORRELATORE

Matr. 704871
CANDIDATO

Anno Accademico 2019/2020

INDEX

CHAPTER 1 – INTRODUCTION

The use of robots in the service encounter context appears to be a promising strategy for retailers and service providers (Grewal et al. 2019). Among the benefits for companies there are cost reductions, enhanced efficiency and effectiveness (van Pinxteren, et al. 2019). Consumers are also better off because these devices increase convenience, availability (van Pinxteren, et al. 2019) and, as it is the case for Technology-Based Self-Service (TBSS), they provide the possibility to avoid social interactions with human service providers, which is extremely valuable in situations in which consumers may anticipate or perceive embarrassment due to service encounters with human agents (Londono, Davies & Elms, 2017).

The aim of this research is to verify whether particular characteristics of customers and of service robots can facilitate or hinder trust in service robots which is crucial for service robot acceptance (Wirtz et al., 2018). Specifically, this study investigates the interplay of customer knowledge of the product or service, anticipated embarrassment in the service encounter, robot anxiety, and robot design in their impact on trust in service robots.

To put it simply: if you look at it from the consumer perspective, the way these variables are connected becomes more intuitive. When thinking about your experience as a consumer there are surely certain fields and product domains about which you consider your knowledge above average and others in which you believe it to be below average.

For instance, if you are passionate about make-up, you might have a deep knowledge of what are the characteristics more relevant in the choice of a lipstick or foundation, you are familiar with the most popular brands, you keep up with trends in the industry, you are probably even knowledgeable about complex matters such as chemical formulas of make-up products. You consider yourself to be an expert in this domain. When you want to buy a new foundation you know how the service encounter will unfold, you have been to the store a million times, you know the jargon so if you need further information you are confident in your ability to ask the right questions and understand the answers. The idea of asking for help does not make you uncomfortable because you do not think that it would put you in an embarrassing situation. You probably do not even need help in the process because you can make the decision on your own.

On the other hand, if you are not so keen about make-up you are probably unsure about what you should look for, you feel overwhelmed by the huge variety of different shades available, you are probably only familiar with a few brands, chemical formulas are completely obscure to you and you are not familiar with the make-up jargon. This means that you are not sure that you can even ask the right questions, let alone understand the answers. You are probably not very confident in your ability to make the right choice on your own and the idea of asking for advice makes you uncomfortable. This is because you fear that most people know more about make-up than you do. You would gladly appreciate a piece of advice to guide your decision, but you do not want to feel judged.

This is exactly where service robots could become beneficial. If once in the store you realized that you could ask for assistance to a service robot, your reaction would depend on your level of expertise in make-up. If you are an expert, you would probably believe that you do not need help with your decision, there is no way that an algorithm can pick a better match than you. On the other hand, if you are not an expert you would probably give it a try because that would allow you to avoid the potentially embarrassing interaction.

Clearly, everything this only holds if you have a positive attitude towards the robot advisor. If you are afraid of it, you probably do not trust it and you want to avoid it. The way the robot looks would play a huge role in determining whether you should fear it or not. For instance, if the robot somehow resembles a human being, maybe it has a face and it can smile at you, you would not find it very scary, and the same thing would happen if you found the robot cute. However, if the robot looked too much like a human being you would probably find it creepy and it might end up scaring you.

From a retailer perspective, using service robots can be a very effective strategy to support customers' decision making. Understanding what factors are crucial in shaping whether robot advice will be complied with or not is essential for succeeding in the implementation of this plan of action. Using service robots may mean providing a large subset of potential customers with more effective advice, thereby increasing chances of a purchase decision, and using service robots in a way that maximizes customer trust in their recommendation may make the difference between a satisfied, returning customer and one who will not be back. This work provides some insights for the use of customer knowledge of products and services as a practical segmentation variable. Furthermore, it shows that using it too crudely, neglecting the role of anticipated embarrassment, robot anxiety and robot design, would make it less effective as a segmentation variable.

More formally, this study analyses whether customer knowledge can be used as an effective behavioural segmentation variable for the identification of a more effective and appropriate use of service robots for specific customer segments. The first hypothesis of this model is that customers with little knowledge of the product or service are more likely to rely on robot advice. Furthermore, this research proposes that this effect is mediated by anticipated embarrassment. The logic behind this reasoning is based on the fact that lack of product and service knowledge has been demonstrated to be an important antecedent of anticipated embarrassment (Miller, 1996). Moreover, Grace (2007) proved that a common coping behaviour triggered by anticipated embarrassment is avoidance of social interactions in order to preserve their self-image. In such instances, Londono, Davies and Elms (2017) have shown that customers are more willing to rely on technology-based self-service because this allows them to receive the product or service without the intervention of a service employee and this allows them to avoid potentially embarrassing interactions. As a consequence, customer knowledge is expected to negatively influence anticipated embarrassment (hypothesis 2) and trust in robot advice. On the other hand, anticipated embarrassment in the service encounter is expected to positively affect trust in robot and reliance to its advice (hypothesis 3).

Moreover, this research investigates the effect of robot anxiety on reliance on robot advice and it analyses what kind of designs are better suited for moderating robot anxiety and increasing robot trust. The application of this kind of technology has been hindered by robot anxiety which decreases service robot acceptance (Nomura et al. 2006; de Graaf & Allouch, 2013; Mende et al. 2019; Mori, 1970; Mori, MacDorman, & Kageki, 2012; Mathur & Reichling, 2016). De Graaf and Allouch (2013) proved that robot anxiety and fear of the robot provoke a sense of discomfort that leads to avoidance of the robot. Thus, the fourth hypothesis of this research predicts that when people are afraid of the robot, they are less likely to trust it and rely on its advice because robot anxiety decreases the positive effect of embarrassment on trust in robot. However, selecting the right kind of design could help increasing trust in robot advice. In fact, Broadbent (2017) has identified robot design as one of the most important elements affecting robot anxiety. In this regard, prior studies concerning the *uncanny valley effect* (Mori, 1970; Mori, MacDorman, & Kageki, 2012; Mathur & Reichling, 2016) demonstrated people have a tendency to prefer robots with anthropomorphized designs with respect to robots with non-anthropomorphized designs. However, when the robot looks almost perfectly like a human being, people experience a sense of uncanniness towards the robot (Mori, 1970; Mori, MacDorman, & Kageki, 2012; Mathur & Reichling, 2016). Mathur and Reichling (2016) proved that the uncanny valley effect influences trust afforded to the robot. As a consequence, this research predicts that people exposed to robots with moderately anthropomorphised designs experience lower levels of robot anxiety (Hypothesis 5a) while people exposed to robots with extremely anthropomorphized designs experience higher levels of robot anxiety (Hypothesis 5b). Another kind of design tested in this study is the cute one. Indeed, according to Nenkov and Scott (2014) and Caudwell, Lacey and Sandoval (2019) this kind of design usually creates associations to naïve creatures, and it decreases perceived treat stemming from the robot. These characteristics are expected to increase trust afforded to cute robots. Thus, this research predicts that people exposed to robots with cute designs experience lower levels of robot anxiety (hypothesis 6).

The importance of developing a deeper understanding of these effects is crucial because service robot's acceptance has been demonstrated to be significantly enhanced through exposure to service robots as well as social influence -i.e. the extent to which the technology is perceived to be accepted by the individual's reference group- (de Graaf & Ben Allouch, 2013). Consequently, it is vital for companies to identify customer segments more prone to interact with and trust service robots to boost social influence and pave the way for service robot acceptance and, as a consequence, for extensive use of service robots in customer care.

This contribution adds to the existing literature is multiple ways. *Firstly*, this work aims at applying insights about different customer knowledge levels to robot trust, which is fundamental for service robot acceptance. Prior literature has identified several customer characteristics affecting service robot trust, acceptance, or intention to use. Among these we find demographic variables such as gender, age, education and field of occupation (Reich & Eyssel, 2013; de Graaf & Ben Allouch, 2013); social influence (de Graaf, & Ben Allouch, 2013); personal traits like extroversion (Ivaldi et al, 2016) and sociability (de Graaf & Ben Allouch, 2013);

dispositional traits associated with anthropomorphism (Reich & Eyssel, 2013); interest in technology and robots (Reich & Eyssel, 2013); robots anxiety (Reich & Eyssel, 2013; van Pinxteren et al. 2019; Mende et al. 2019; de Graaf & Ben Allouch, 2013); and expectations of robot performance and required effort (de Graaf & Ben Allouch, 2013). However, customer knowledge of the service or product and coping behaviours triggered by the negative emotional state caused by lack of customer knowledge have not been analysed yet in this context. This investigation is extremely relevant because it introduces a new behavioural segmentation variable shaping service robot acceptance. Moreover, customer knowledge can be more easily estimated (for example through customer profiling) with respect to behavioural traits that have been identified by prior literature such as extroversion and sociability and could thus be more practical for the use of service robots.

Secondly, this work investigates a coping behaviour triggered by embarrassment that had received little attention so far but that could provide some useful insights both about service robot acceptance, and about the service encounter more in general. Indeed, literature on embarrassment in the service context has identified lack of customer knowledge to be one of the main determinants in the process (Grace, 2007), as it is also supported by both *dramaturgic* (Higuchi &Fukada, 2002) and *social evaluation (*Miller, 1996) *theories* of embarrassment. This reinforces the idea that novices are more likely to engage in a series of coping behaviours. Because coping behaviours triggered by anticipated embarrassment can be extremely harmful for service providers (Grace, 2007) it is important to understand whether providing an alternative to human interaction leads to better advice compliance when it comes from a source different from humans. In addition to that, whether these mechanisms affect trust in technology-based self-service and in particular in robot advice has not been analysed yet.

Thirdly, an important theoretical contribution of this work pertains to the role of trust of service robot. Although some papers analysed this variable (Mori, 1970; Mori, MacDorman, & Kageki, 2012; Mathur & Reichling, 2016; van Pinxteren, et al. 2019) the majority of studies on robot acceptance focused on intention to use or actual use of service robots. It can be argued that the importance of trust in service robot and service robot advice is crucial both because trust can be construed as underpinning intention to use (van Pinxteren, et al. 2019) and because trust affects the extent to which service robots are able to influence customers' behaviour through compliance with advice (Wirtz et al. 2018). This has important implications in terms of purchase, repurchase, satisfaction and loyalty. I argue that understanding what elements increase customers' trust in robots allows for a more effective use of service robots. Indeed, it is impractical to focus on elements that increase intention to use and interact with the service robot, neglecting elements that increase trust in its advice in the service context. Eventually, the goal of using service robots in customer care is supporting customers and influencing their purchasing behaviour. If trust in robot is not fostered, this objective cannot be achieved.

Fourthly, this work contributes to literature on human vs. algorithmic decision-making and advice taking in this context (Dawes, 1979; Dawes, Faust & Meehl, 1989; Yeomans et al. 2019; Buell & Norton, 2011). Indeed, prior literature on advice taking identified a suboptimal integration of external advice (Dawes, 1979; Dawes, Faust & Meehl, 1989; Yeomans et al. 2019) and this effect seems to be even amplified when the source of advice is algorithmic rather than human (Dietvorst, Simmons, & Massey, 2015). In fact, algorithms have been proved to outperform humans in various judgment tasks but despite this, humans have a tendency to distrust them (Dawes, 1979; Dawes, Faust & Meehl, 1989). This implies that humans miss the opportunity to improve accuracy of decision-making because they have a bias for discarding algorithm advice. As a consequence, it is crucial to identify factors that may lead to higher trust in external advice (Yeomans et al. 2019). In the context of robotics, it is possible that robot advice is perceived as algorithm advice and thus discarded. However, physical presence of the machine could lead to higher compliance to robot advice when compared to general algorithm advice. In support of this reasoning, Buell and Norton (2011) discovered that enhancing resemblance to human behaviour and to human beings can lead to higher compliance to algorithm advice. Thus, it can be argued that robots, because they are more similar to human beings with respect to algorithms that lack a physical body, can achieve higher advice compliance.

Fifthly, this work bridges studies on algorithmic advice and robot advice. In particular, this study demonstrates that findings from algorithm appreciation and aversion (Dietvorst, Simmons, & Massey, 2015; Logg, Minson & Moore, 2019) are applicable and extremely relevant in the context of reliance to robot advice. One common finding of these apparently conflicting theories, namely experts' tendency to discard algorithmic advice, seems to suggest that novices are more promising customers in terms of compliance to service robot's advice. Indeed, although Dietvorst, Simmons, and Massey (2015) are more sceptical concerning the extent to which people's decision-making can be influenced by algorithmic suggestions with respect to Logg, Minson and Moore (2019), they both agree that novices are less reluctant to integrate algorithmic advice in their decision-making process compared to experts. This finding implies that implementing technology-based self-service that includes algorithm-based suggestions may be more effective for customers who have little expertise in the product or service. However, a connection between compliance with algorithmic advice and compliance with robot advice has not been studied to the date.

Sixthly, and lastly, this work contributes to the discussion on robot design and its role on robot anxiety as it aims at identifying appropriate designs that foster robot trust and compliance to robot advice. In particular, this work applies findings from literature on anthropomorphism of service robots design (de Graaf & Allouch, 2013; Broadbent, 2017; Chandler & Schwarz, 2010; Aggarwal & McGill, 2007; Epley, Waytz & Cacioppo, 2007; Waytz, Heafner, & Epley, 2014; Siegel, Breazeal & Norton, 2009; van Pinxteren et al. 2019) and cute design (Demeure, Niewiadomski & Pelachaud, 2011; Nenkov & Scott, 2014; Caudwell, Lacey, & Sandoval, 2019; Sprengelmeyer et al. 2009; Broadbent, 2017; Waytz, Heafner & Epley, 2014) to test whether these designs manage to reduce robot anxiety which could otherwise reduce the extent to which both novices and experts would be comfortable in interacting with robots. The reason why these elements need to be considered in a relevant model of weight on robotic advice is that if people exhibit fear of robots, they can be expected to be less likely to comply with robot advice. As a consequence, it is crucial to select the most effective designs in order to minimize robot anxiety.

The structure of this study is as follows. The first chapter presents the model of the study and it provides an introduction about the service robots industry and state of the art in the section 1.1. This section provides evidence concerning the potential of this industry which is expected to dramatically grow in the coming years due to technological changes that are expected to substantially improve performance of service robots. Moreover, section 1.2 introduces the beauty industry which is the field of application of the model, and it shows why service robots represent a potential fit for this industry. De facto, this industry has witnessed a substantial increase in terms of products available for consumers which have been proved to create confusion in non-expert customers (Uzzi, 2019). To address this problem, the biggest brands in the industry have started to include AI-powered recommendation systems to support customers throughout their customer journey (Uzzi, 2019). However, these technologies are not likely to thoroughly engage the customer (Grewal et al. 2019). In addition to that, *algorithm aversion theory* predicts that these kinds of recommendations are sub-optimally integrated by individuals (Dietvorst, Simmons, & Massey, 2015). This suggests that this particular industry is ready to implement service robots in customer care and this could be a solution to address the limitations of currently used technologies.

The second chapter of this research provides a literature review of the main themes touched upon on this introduction. Section 2.1 is dedicated to customer knowledge and it illustrates the reasons why customer journeys of consumers with different levels of expertise in the product or service are different. In particular, the section shows how different levels of customer expertise produce a different set of cognitive tools available for decision making which leads to differences in decision-making processes, outcomes, mental shortcuts, confidence in the decision, preferences for recommendation systems and more.

Section 2.2 presents prior literature's findings about embarrassment and anticipated embarrassment. The section defines the construct as distinct from related concepts such as shame and humiliation. The sub-chapter shows that lack of customer knowledge can generate anticipated embarrassment (Miller,1996) because it is likely to trigger the mental processes discussed in both *social evaluation theory* (Miller, 1996) and *dramaturgic theory* (Higuchi & Fukada, 2002) which construe two important antecedents of embarrassment and anticipated embarrassment. In addition to that, the section highlights two important concepts which predicts that embarrassment has a great impact on consumer behaviour: *emotional loss aversion* (Baumeister et al. 2001) and the *spotlight effect* (Gilovich & Savitsky, 1999). The last part of the embarrassment section discusses related coping behaviours investigated by Grace (2007) and how technology-based self-service has been proved to be beneficial in this context for the purchase of embarrassing products, suggesting that service robots could be beneficial for addressing potentially detrimental embarrassment coping behaviours (Londono, Davies & Elms, 2017).

Section 2.3 introduces and defines robot anxiety (Nomura et al. 2006). It discusses its consequences (Mende et al. 2019) and it analyses its antecedents. Among these there are the *uncanny valley effect* (Mori, 1970; Mori, MacDorman, & Kageki, 2012; Mathur & Reichling, 2016), category confusion (Broadbent, 2017), concerns for job loss threats (Waytz & Norton, 2014), concern for threats to human identity (Mende et al. 2019), and negative associations to diseased or dead bodies (Broadbent, 2017; MacDorman, 2005).

Section 2.4 describes the importance of robot design in shaping individuals' attitudes towards robots and it is divided into 3 sub-sections based on three important design characteristics that have been proved to be crucial in this context: physical embodiement (sub-section 2.4.1), anthropomorphism (sub-section 2.4.2) and cuteness (sub-section 2.4.3).

The last section of chapter two is dedicated to trust in robot advice (section 2.5). The section begins with an explanation of the processes that lead to discount others' advice such as *egocentric discounting (*Yaniv & Kleinberger, 2000), *anchoring and insufficient adjusting* (Tversky & Kahneman, 1974), *egocentric bias* (Krueger, 2003) and *negativity bias* in advisor's reputation formation (Yaniv & Kleinberger, 2000). The section furthermore shows that distrust in advice can be extremely detrimental to accuracy of decision making and that this effect is further amplified when the source of the advice is an algorithm as opposed to a human (Yeomans et al. 2019; Dietvorst, Simmons, & Massey, 2015). However, Gino and Moore (2006) demonstrated that when the task is perceived as difficult, people are less confident in their ability to perform the task independently and tend to seek for advice. This finding suggests that novices, who are more likely to perceive service-related tasks as difficult because of their lack of service expertise, may be more likely to rely on advice. Lastly, the section discusses the importance of robot trust for service robot acceptance and it investigates prior literature's findings about the effect of robot design on robot trust.

The last chapter of this research contains the model, the procedure, the results and the discussion of the experiment of the study. Indeed, section 3.1 describes the model and provides a detailed description of the hypothesis as well as the reasonings behind them.

Section 3.2 discusses the methodology for testing the model. Section 3.2.1 describes the procedure of the pre-test that has been conducted through an online survey with 130 participants to make sure that the robot designs that were to be used in the main study were perceived as expected based on criteria provided by prior literature. Five robot designs have been tested, to do so five comparable videos of five robots have been edited to show the very same actions performed by each robot, even the music in the background has been homologated to avoid biasing perceptions of the designs. A robot named Cruzr was expected to be perceived as neither anthropomorphised nor cute so that it could have been used as control condition in the main study. A robot named *Asimo* was expected to be perceived as moderately anthropomorphized but not cute, so that it could have been used as the moderately anthropomorphised condition in the main study. A robot named *Kuri* was expected to be perceived as not anthropomorphized but cute, so that it could have been used as the cute condition in the main study. A robot named *Sophia* was expected to be perceived as extremely anthropomorphized but not cute, so that it could have been used as the extremely anthropomorphised condition in the main study. And finally, a robot named *Pepper* was expected to be perceived as both anthropomorphized and cute, so that it could have been used as the anthropomorphised and cute condition in the main study. The section also describes the way the online survey has been conducted including videos and questions that participants have been exposed to.

Section 3.2.2 describes findings from the one-way ANOVA and post-hoc analyses conducted on SPSS of the pre-test data. The first four designs have been confirmed to be perceived exactly how it had been anticipated. However, the last one, Pepper, that was expected to be perceived as both cute and anthropomorphized, did not exhibit significant differences in terms of perceptions of these dimensions with respect to the control condition. For this reason, it has been excluded from the analysis of the main study.

Section 3.2.3 describes the procedure of the main study that has been conducted through an online experiment with 374 participants to test the hypotheses of the model. The section also describes the way the online experiment has been conducted including the videos, photos, questions, and the decision task that participants have been exposed to. In practice, participants have been asked to rate their knowledge in the domain of make-up, in particular, the study assessed their expertise with foundation. After that, they have been asked to rate the extent to which they would have felt embarrassed in a situation in which they consulted a shop assistant for buying the right shade of foundation for their skin tone. After that, they have been shown a photo of an arm with various shades of foundation on and they have been asked to choose the shade that they thought they would have bought if they had to decide on their own. The experiment continued randomly showing each participant one video of a robot design selected through the pre-test. After that, participants have been told to imagine that the robot had scanned their skin tone and advised them to select one particular shade. Moreover, participants have been tested for the robot anxiety generated by the particular condition they have been assigned to. After that, they have been asked to make their final decision, fill in an attention check question to make sure they remembered the advice provided, and they have been asked to provide some demographics.

Section 3.2.4 provides the findings of the analysis conducted on SPSS with PROCESS v3.4 model 18 to test the hypothesis of the model which is a second stage conditional moderated mediation (Hayes, 2017). The first four hypothesis have been confirmed demonstrating both the mediating role of anticipated embarrassment in the relation between customer knowledge and trust in robot advice, and the moderating role of robot anxiety on this effect. However, the hypotheses concerning the effect of design on robot anxiety have only partially been confirmed as hypothesis 5b has been proved to be significant suggesting that extremely anthropomorphized designs significantly lead to lower levels of robot anxiety. On the other hand, although moderated anthropomorphized designs and cute design triggered lower levels of robot anxiety in participants, these differences were not proved to be significant.

The last section of the research, section 3.3 includes the discussion concerning the findings of the study including the theoretical contribution (section 3.3.1), managerial contribution (3.3.2) and limitations and suggestions for further research (section 3.3.3).

1.1 – SERVICE ROBOTS INDUSTRY AND STATE OF ART

Service robot industry has been steadily growing in the last years. According to the global report of robot industry of Deloitte Insights one million robots are expected to be sold in 2020, half of which are expected to be in the form of professional service robots (Casey, Stewart & Wigginton, 2020). The document forecasts that these robots are expected to generate revenues for approximately US$16 billion which represent an increase in revenues of 30% with respect to 2019[1]. Moreover, professional service robots' industry is growing much faster than industrial robots' industry. The former is expected to outweigh the latter both in terms of units purchased in 2020 and of revenue generated in 2021. It should be noted that these forecasts are not motivated by an expected contraction of industrial service robot market but rather by a significant growth of professional service robots market boosted by two major changes in the industry. Casey, Stewart and Wigginton (2020) believe that industrial robots' industry will keep on growing and will produce US$18 billion in revenue in 2020 which represent a 9% increase with respect to 2019. However, according to the authors, two technological advances are expected to have a greater positive impact on service robots' industry with respect to industrial robots' industry (Casey, Stewart & Wigginton, 2020).

In the report produced by Casey, Stewart and Wigginton (2020), the two major trends affecting the service robots' industry are identified: the improvement of wireless connectivity through 5G network technology and the falling price of cutting-edge AI chips. In fact, the authors argue that, before 5G, reliable connectivity that did not constrain service robots' mobility was a difficult issue. Two solutions were available before 5G networks: wired connectivity and 4G wireless networks, however, these two technologies faced an important trade-off. On one hand, via-wire connectivity is highly reliable, but it constrains service robots' movements. On the other hand, 4G wireless networks allows for greater robot mobility but it has higher latency (which implies lower reliability) and this constrains the ability of the robot to quickly react to inputs. 5G network is a wireless solution that delivers sub millisecond latencies. This means that 5G networks allow for a fast reaction time while not compromising service robots' mobility. Thus, Casey, Stewart and Wigginton (2020) argue that this technological advance will have a huge impact on service robot industry but a minor one on industrial robots' industry because in the latter industry wired solutions are still outperforming 5G networks in terms of costs and robots mobility is not a big concern because the majority of industrial robots operate in fixed positions.

The second crucial trend described in the report is the advance in AI chips in terms of both improvements of service robots' performance and decrease of power consumption (Casey, Stewart & Wigginton, 2020). Cutting edge chips specifically designed for AI processing are highly energy-wise efficient and can processes a greater amount of information. This also has an implication on the amount of chips needed for each unit which eventually leads to fewer technical constrains in service robots' design solutions. These chips yield higher

[1] See appendix a, figure 1 - *Annual global robot unit sales for enterprise use, 2016-2020* (Casey, Stewart & Wigginton, 2020)

potential in the service robot industry as opposed to the industrial robots 'one because industrial robots do not usually require processing a huge amount of data as service robots do during customers' interactions. In addition to that, industrial robots usually have room for several chips and design is not as important as in service robots. While most service robots engage in Huma-Robot-Interactions which have been demonstrated to be favoured by specific designs, industrial robots rarely interact with people. As a consequence, the study conducted by Casey, Stewart and Wigginton (2020) predicts that the combination of these technological developments could solve several problems that have limited the applicability of service robots so far.

Moreover, according to a research published by Statista (2019) an important trend that affected the spread of service robots is the aging of the population and the increasing demand for specialized nursing staff. Service robots provide support to specialized workers in this field narrowing the gap between demand and supply and increasing the efficacy of nursing staff. Moreover, robot-assisted surgery is expected to take hold in the near future due to higher precision, flexibility and control with respect to traditional devices. The study shows that in this context America dominates the market and it is also the worldwide leader in the commercial service robotic market, while Europe dominates the logistics robot market and Asia Pacific dominates the market for household robots and customer service robots. In particular, customer service robots are deployed in contexts such as telepresence, hospitality and customer care. According to the report, in 2019 sales worldwide of these robots, also termed public relations robots, reached 309 million US dollars, of which 222 million US dollars accrue to Asia Pacific, 56 million US dollars accrue to Americas, 25 million US dollars accrue to Europe and 6 million US dollars accrue to other regions[2]. Experts believe that although this market in Asia Pacific is reaching a mature stage (which is expected to experience a stagnant growth in the next years), markets in America and Europe are rapidly expanding and will lead growth in the market which is expected to reach 409 million US dollars worldwide in 2021 (Statista, 2019).

According to Leroi-Werelds (2019) recent developments in automation are set to completely revolutionize several industries. This change is expected to be so dramatic that Wirtz et al. (2018) have defined it as the "Fourth industrial revolution" where technology is used to not only improve, but even replace work currently done by human beings. Leroi-Werelds (2019) argues that historically, services have been characterized by the exchange and interaction between customers and frontline employees. However, frontline service technologies and in particular technology-based self-service devices are crucially modifying service encounters and the extent to which service employees are engaged in them (Leroi-Werelds, 2019).

Kinard, Cappella and Kinard (2009) defined technology-based self-service as technological interfaces that allow customers to produce or customize their service experience without the direct interaction with a service employee. Their use has increased significantly in the last decades. Among the most common TBSS applications there are airline ticket kiosks, self-scanning checkout stations and automated hotel checkout

[2] See appendix A, figure 2- *Sales volume of public relations service robots by region* (Statista, 2019)

procedures (Kinard, Cappella & Kinard, 2009). The authors argue that these devices could become one of the main interactive interfaces in several retail contexts to facilitate transactions with customers. Among the benefits of these technologies identified by Kinard, Cappella and Kinard (2009) there are the optimization of efficiency in service delivery and reduction of personnel costs. In addition to that, Londono, Davies and Elms, (2017) proved that these devices even reduce social anxiety and embarrassment of customers in certain contexts. The authors even suggested that this option should be the main one if customers are expected to perceive or anticipate embarrassment in the purchase of certain goods. However, the beneficial effects of the use of TBSS for customer embarrassment avoidance has only been proposed for the purchase of embarrassing goods (e.g. condoms) (Londono, Davies & Elms, 2017). Be it as it may, the effects in situations in which embarrassment comes from customer's lack of familiarity with the product or service have not been analysed yet. In addition to that, no prior study has been conducted on the role of anticipation of embarrassment on a specific application of TBSS, namely autonomous service robots.

Kinard, Cappella and Kinard (2009) investigated several factors affecting the adoption and trust of TBSS both positively and negatively. Among the elements identified in their research that facilitate TBSS acceptance there are attitude towards technology, consumer readiness to use the specific TBSS technology and anticipated satisfaction with the technology's performance. For what concerns elements that undermine acceptance of TBSS, the main ones are technological anxiety, need to interact with other people and interactive social influence (Kinard, Cappella & Kinard, 2009). However, it is still uncertain whether anticipated embarrassment caused by the service encounter could lead to higher trust in TBSS.

An important technology used in many TBSS is Artificial Intelligence (AI). AI technologies are able to replicate the way humans think and it includes visual recognition, problem solving, learning, speech recognition, natural language processing and so on (Leroi-Werelds, 2019). According to Huang and Rust (2017) four main types of AI technologies' service tasks can be identified: mechanical, analytical, intuitive, and empathetic. Mechanical AI technologies improve accuracy of human performance and they increase consistency of service quality and they are usually involved in simple tasks. An example of a mechanical AI technology provided by the authors is the TBSS "Create your Taste" kiosks implemented by McDonald. Analytical AI are defined by Huang and Rust (2017) as technologies that make use of algorithms that allow them to learn and find insightful information autonomously i.e. without being programmed to look for specific information. These kinds of technologies make use of big data analysis and are widely used in a variety of industries. Intuitive AI technologies are used for dynamic personalization that learns preferences of consumers through the observation of their behaviour over time. For instance, Netflix highly relies on this kind of algorithms to make recommendations to its customers integrating both insights gained about individuals' behaviours as well as behaviour of other customers with similar tastes (Yeomans et al. 2019). Lastly, Huang and Rust (2017) define empathetical AI technologies as devices able to detect human emotions and respond accordingly. This ability is crucial in contexts in which algorithm-based devices need to interact and empathize with human beings, in fact, social robots make wide use of this kind of AI (Huang & Rust, 2017).

Autonomous robots represent a kind of TBSS able to carry out complex interactions with customers that make use of AI (Huang & Rust, 2017). Broadbent (2017) defined the autonomous robot as a machine that can operate certain tasks without the need for continuous human guidance and control. Reich and Eyssel (2013) provided a classification of autonomous robots in two sub-categories, namely personal (or domestic) service robots and professional service robots.

According to Reich and Eyssel (2013) domestic robots are produced for personal use, they usually provide assistance and entertainment. In such context, the study by Reich and Eyssel (2013) demonstrated that several demographic and psychological variables play a role in attitudes formation towards the robot. Specifically, the authors proved that women are more likely to exhibit robot anxiety and negative attitudes towards robots. Furthermore, interest in science and technology as well as previous experiences with robots caused participants to exhibit low levels of robot anxiety and elicited overall positive attitudes towards robots in the domestic environment (Reich & Eyssel, 2013). Moreover, the three psychological determinants of anthropomorphism (that will be further explained in the anthropomorphism chapter, section 2.4.2), i.e. need for cognition, need for control and chronic loneliness also positively affected attitudes towards robots. In general participants of the study conducted by Reich and Eyssel (2013) recognized a certain appeal associated with the robot assistance in their tasks, however the majority of them did no appreciate the idea of having a robot in their homes justified this opinion with the belief that such a complex technology required careful management. It is possible that, because consumers are not familiar yet with this technology, they are not ready for interacting with them in the domestic environment and this could explain their reluctance in adopting personal robots (Reich & Eyssel, 2013). However, the authors do not exclude readiness for interactions with autonomous robots outside the domestic environment and this suggests that service encounter might represent a more favourable context for favourable robot interactions.

Reich and Eyssel (2013) define professional robots as robots used in industrial (physical production, e.g. in the car manufacturing industry) and commercial (retail or customer interactions to facilitate technology-based self-service) domains. Within the context of professional commercial robots, also referred to as service robots, Wirtz et al. (2018) made a distinction between physical service robots like *Pepper* and virtual service robots also called text-based or voice-based virtual assistants. An example of a voice-based virtual assistant is Amazon's *Alexa* (Wirtz et al., 2018). This paper focuses on commercial professional robots that are characterized by physical presence.

According to Leroi-Werelds (2019) commercial professional service robots can improve service quality because they deliver services in a more consistent and homogeneous manner with respect to traditional service employees. In addition to that, preparing a robot to be able to meet customer needs requires very little time compared to the time required for employee training (Wirtz et al., 2018). Ivanov and Webster (2019) suggest that the use of robotics, AI, Internet of things and automation technology will speed up and play an important role even in service industries that are traditionally perceived as “people businesses”. According to the authors factors such as aging of the population, low birth rates and advances in these kinds of technologies lie at the basis of this huge market shift (Ivanov & Webster, 2019). The application of service robots in commercial settings and especially their interactions with customers, has been analysed by several authors and it seems more promising than the application of personal robots at the moment (Reich & Eyssel, 2013).

Wirtz et al. (2018) defined service robots are machines capable of carrying out complex tasks and autonomous decision-making in service provision contexts. They can adapt to situations and learn from previous experiences through machine learning. The authors suggest that their introduction on a mass scale could potentially revolutionize interactions with customers and reshape completely the nature of services. Indeed, they offer benefits for service providers such as cost reduction, increased customer satisfaction and brand loyalty but also for consumers such as flexibility, convenience, efficiency, and availability. They represent the newest generation of technology-based self-service and their main advantage with respect to other TBSS according to Wirtz et al. (2018) is that they are able to take part in interactions much more social in nature. Service robots’ technological advances allow them to imitate human-human interactions. In fact, service robots are able to create to some extent a form of automated social presence during the service encounter (Wirtz et al. 2018). In other words, they are able to make the customer feel as if he is interacting with a social agent and although he recognizes that robots are not the same as human beings, people do tend to behave in a similar manner with robots and humans. According to Wirtz et al. (2018), this perception of similarity between robots and humans elicits a wide variety of reactions, some —but not all— of which are similar to reactions elicited in human-human interactions. In fact, because these Human-Robot Interactions (HRIs) are very similar but not identical to human-human interactions, they can cause category confusion and discomfort that should be handled carefully (van Pinxteren et al. 2019).

There are several industries in which HRIs are not as crucial. For instance, an important field of application of autonomous robots is in the manufacturing, indeed many factories have initiated a process of coproduction of humans and autonomous industrial robots leading to significant increases in productivity (Askarpour et al. 2019). Agriculture is another sector that highly benefits from the use of autonomous robots especially in the harvesting phase (Xiong et al. 2019). The biggest companies developing these kinds of robots are AGROBOT, OCTINION and Harvest CROO (Xiong et al. 2019). Efficiency and productivity of supply chain management and logistics have significantly improved through digitalization and the use of the so-called smart warehousing which makes use of autonomous robots (Mahroof, 2019). According to Mahroof (2019), A company significantly committed in the use of these kinds of systems is Amazon. In the military sector, the use of autonomous, semiautonomous robots, mechanized exoskeletons as well as drones is increasing for dangerous tasks in order to enhance safety for soldiers (Altmann & Sauer, 2017). However, it should be noted that many authors have raised ethical issues stemming from using robots in such a context (Altmann & Sauer, 2017).

One of the first interactions between autonomous robots and humans has been in the form of social robots in the healthcare industry (Broadbent, 2017). In the field of healthcare of older people, robots have been used to provide help with physical tasks (for example walking and carrying heavy objects), cognitive issues (playing memory games, extremely beneficial especially for patients affected by dementia), health management (monitoring blood pressure and detecting falls), and psychological issues (providing companionship) (Broadbent, 2017). Examples of robots used in this field include Paro, iRobi and Cafero (Broadbent, 2017). According to Hoa and Cabibihan (2012), another beneficial application of robots in the healthcare pertains social robots used with children in the autism spectre. These robots are used to help children learn how to detect emotions and how to interact with people. The authors argue that the rationale for the use of these robots lies in the fact that because robots are more predictable than human beings and exhibit fewer emotional states, they are easier to understand for children with this condition. These robots help kids practice their social skills, they provide feedback as well as encouragement and they tend to be designed in such a way that they do not scare children. An example of a robot used in this field is *Nao* (Hoa & Cabibihan, 2012). This robot has also been used in the health management education context leading to brilliant results especially in educating kids with diabetes (Broadbent, 2017). In the field of education AI and machine learning has been used to develop technology-based learning environments to personalize student's learning process and the success of these devices suggest that there is room for adaptive technology systems in future education (Walkington & Bernacki, 2018).

Although more recent, the use of autonomous robots is increasing in various fields and they are expected to become established in the service context (Broadbent, 2017). Service robots need to interact with customers in various situations and this requires a more complex system to enable the robot to behave correctly in each situation (Wirtz et al., 2018).It should be noted that acceptance of service robots in the service context is not the same throughout the world (Broadbent, 2017). Indeed, Broadbent (2017) argues that in Asia it is not uncommon to see robots in hospitals and retirements home as well as kindergartens and shopping malls. In western countries robot acceptance has been slower because of several factors, however some autonomous robots like Roomba are widely accepted for vacuuming and some companies are making use of autonomous robots for deliveries (Broadbent, 2017).

Moreover, important AI applications in context of provision of legal services as well as trading on financial markets represent important opportunities for robotics according to Ivanov and Webster (2019). The authors see a great potential for the use of service robots in customer care especially in the context of travels, tourism, and hospitality. In their study they provide a thorough analysis of the way service robots and AI powered technologies are being increasingly used in the industry of hospitality. Text-based virtual assistants allow customers to book trips through chatbots, they receive recommendations on online travel agency websites based on AI recommendation systems and it is not uncommon for airports to provide travellers with the possibility to use TBSS check-in devices as well as automated passport control. In addition to that, some hotels in Asia are now using robots for check-in procedures and greetings of guests. Room cleaning can be now performed by autonomous robots and even room service can be now delivered by robots. Robots used in travels, tourism and hospitality robots differ significantly in their degree of autonomy, intelligence, and interactivity with customers. Some robots do not interact at all with people others on the other hand, are able to carry out complex Huma-Robot-Interactions. For instance, the authors mention a robot called *Pepper* , produced by Softbank Robotics, that has been used both in hotels and in airports and it is able to understand and process not only several languages but it is even able to detect some human emotions and to respond appropriately. Another example provided by Ivanov and Webster (2019) is a similar robot called *Amy*, used in restaurants as a waiter.

It should be noted that robotics in customer service is still at an early stage of its development but it could lead to significant success not only in terms of cost reduction and customer convenience but even in terms of customer satisfaction and engagement (Ivanov & Webster, 2019). According to Wirtz et al. (2018) several industries have already moved towards a more digitalized and automated business and are thus better suited for adopting service robots for customer care.

1.2 - BEAUTY INDUSTRY AND TECHNOLOGY

While the cosmetic industry has been revolutionized by the introduction of AI and industrial robots, it still yields wide potential for a greater use of robots in customer care. For example, the biggest player in the industry, L'Oréal, is committed to becoming the leader in beauty tech, suggesting that the industry is becoming increasingly open to new technologies (L'Oréal.com, 2020). According to Uzzi (2019), one of the reasons why cutting-edge technologies are extremely relevant in this field is that consumers are often unsure about what products they need and asking for professional advice in store can cause discomfort in customers. Many companies have started addressing this problem by integrating in the shopping experience AI-powered recommendation systems to guide consumers' decision making (Uzzi, 2019; Grewal et al. 2019). According to Grewal et al. (2019) retailers in this industry make use of an increasing variety of technologies aimed at enhancing operations, improving customer experience and supporting customers in the decision-making stage. Companies experimenting new technologies are experiencing great success in the field (Grewal et al. 2019). Thomas (2019) identified four technological changes based on AI- powered recommendations that are set to revolutionize this highly competitive industry and that seem to suggest that the industry is moving towards a more digitalized and automated business: printed makeup, try-on apps, smart skin care tools and personalization through AI.

Printed make-up refers to devices like *Opté*, developed by Procter & Gamble and that will be launched in 2020, that scans customers' skins and applies make up to hide age spots and other blemishes (Thomas, 2019). The product uses a small camera that detects through a microprocessors irregularity of the skin and applies foundation through a micro printer (P&G.com, 2019). This device is entirely automated and requires little knowledge by the user in order to correctly conceal irregularities of the skin (P&G.com, 2019). In addition to that, the selection of the foundation shade is entirely made by the device (P&G.com, 2019) and this further simplifies the entire process of purchase and consumption.

Thomas (2019) describes try-on apps as smartphone applications that make use of augmented reality and allow customers to virtually try on cosmetic products. According to the author, technological advances in face recognition allow for more accurate digital overlays which result in more realistic images. For instance, Sephora launched its *Virtual Artist* which is a TBSS in the form of a smart kiosk and smartphone app that guides customers in the selection of lipsticks and eyeshadows shades, it shows tutorials on how to apply the products and it proposes products that better match customers' skin tone (Thomas, 2019). A new feature of this TBSS includes the possibility to find the perfect shade of foundation scanning a photo of the customer thanks to a new AI-powered technology called *Color Match* (DeNisco Rayome, 2018). This feature was developed with a collaboration with ModiFace, a company specialized in augmented reality solutions for beauty products (DeNisco Rayome, 2018). According to DeNisco Rayome (2018), *Virtual Artist* helps customers choose between the overwhelming selection offered by the retailer with the goal of simplifying the purchase of products such as foundations which are typically difficult to choose for less expert customers. The author mentions, another important technology used for helping customers decide the best foundation shade called *Color IQ*, which was developed by a partnership of Sephora and Pantone. This device scans the customer's skin it assigns the customer a certain Color IQ number, and it suggest the shades that represent a better match for her particular code (DeNisco Rayome, 2018). According to DeNisco Rayome (2018), customers responded pretty well to these kinds of AI-powered recommendations both in-store and online and the beauty industry is now adapting to this new trend developing continuously improving devices for these recommendation systems.

According to Thomas (2019), smart skin care tools are devices able to scan customers' skin and to provide advice concerning skin care products. An example provided by the author is the smart mirror developed by New Kinpo Group called *HiMirror*, another one is Olay's *Skin Advisor* that is a smartphone app that allows customers to visualize what their skin will look like in the future. What is revolutionary about this technology is that it allows for personalized advice and privacy which decreases instances of embarrassment for consumers (Uzzi, 2019).

Thomas (2019) argues that personalization through AI allows consumers to customize products and create tailor-made shades that perfectly match customers' skin tone . An example of this innovation according to him is Lancôme's *Le Teint Particulier* which is a machine to be used in store to create tailormade shades of make-up. Interestingly, personalization of beauty products is not a trend that only belongs to high-end beauty products and personalization will soon not be only possible in-store (L'Oréal.com, 2020). Indeed, customers will soon be able to create tailored skin care products, foundation, and lipstick at home with *Perso*, a tiny bot developed by L'Oréal that will be launched in 2021 (L'Oréal.com, 2020). Perso is a smart device powered by artificial intelligence that learns constantly through machine learning (L'Oréal.com, 2020). For what concerns skin care products, the device scans customer's skin through a software called ModiFace technology, takes into consideration customers' top skin care concerns and priorities, it assesses important environmental factors through Breezometer geo-location data, and it dispense the perfect formula for each customer combining ingredients in its cartridge system. Tailored foundation is produced in a similar manner thanks to it precise shades finder tool. For what concerns lipstick customization, Perso allows consumers to match their lipstick with their outfits and even to reproduce lipsticks in other people' pictures. This technology allows for a significant waste reduction and it allows Perso to perfectly meet each customer's needs (L'Oréal.com, 2020). Obviously, this also simplifies the whole customer journey as shade selection is no longer an issue and seasonal variations of skin tones no longer require the purchase of a new product (L'Oréal.com, 2020).

It seems clear that digitalization and AI-powered recommendations are becoming increasingly important in various aspects and trends that are shaping the beauty industry. AI-powered recommendations entail several benefits as it has been demonstrated that algorithms often outperform experts, but they also face important challenges in terms of advice compliance. In general, algorithms can improve humans' decision making in certain domains because they are consistent, they have perfect memory, they are not subject to biases and they do not experience fatigue that decreases accuracy (Dawes, Faust & Meehl, 1989). According to Dawes (1979) this does not mean that algorithms and linear models should substitute humans, rather they should complement human expertise. The author argues that algorithms are better than humans in sticking to rules, but such rules, at least in the case in which human judgment is what algorithmic linear models are based on, can only be defined through human expertise. According to Yeomans et al. (2019), algorithms are being increasingly used to make recommendation and predict people's preferences in a wide variety of fields such as films, books, restaurants and various products. The authors argue that these recommendation systems can have important effects on consumers' behaviours as well as on companies' profitability. But when it comes to recommendations, people naturally trust more people that are close to them (family, friends, etc…) and in general even people that they do not know, with respect to algorithmic recommendations. Indeed, the series of study conducted by Yeomans et al show that people are reluctant to comply with advice that comes from an algorithm even in instances in which adhering to algorithmic advice significantly increases accuracy of decision- making. These issues are matters that need to be addressed in the beauty industry to make sure that the digitalization that is taking place is in line with customer needs. Developing recommendations systems that are not listened to by customers could be costly and ineffective.

The potential for these devices in this industry is high because Yeomans et al. (2019) demonstrated that algorithms outperform humans in terms of accuracy of preference recommendations, even if the human recommender and the person receiving the advice have been knowing each other for many years and they are related. This holds true even in domains in which humans are expected to excel with respect to algorithms such us humour (Yeomans et al. 2019). However, when people exhibit algorithm aversion, they miss the opportunity to get more accurate recommendations. As a consequence, it is crucial for beauty industry retailers to design recommendations systems that minimize algorithm aversion in order to increase compliance with algorithmic advice.

According to Grewal et al. (2019) the two most important characteristics of cutting-edge technologies used by retailers to enhance customer experience are convenience and social presence. The authors state that a technology is said to increasing convenience for customers when it improves or simplifies at least one of five dimensions: decision, access, transaction, benefit, and post-benefit. While it is obvious that AI-powered recommendation systems and in general many of the cutting-edge technologies used in the beauty industry enhance convenience for customers because most of them allow customers to receive quick and accurate personalized suggestions or even products, the same cannot be said about social presence according to Grewal et al. (2019). The authors argue that a technology that elicits social presence is a technology able to elicit the perception that a human being is present. Among the technologies described above, only two are able to produce social presence because they do not involve human beings in their processes either physically or virtually present, nor they make use of devices that are able to elicit social presence in absence of human beings. These two exceptions are Lancôme's *Le Teint Particulier* and Sephora's *Virtual Artist.* Indeed, *Le Teint Particulier* requires shop assistants to be physically present in the processes and this positively affects social presence. Sephora's *Virtual Artist's* is able to elicit perceptions of social presence by allowing customers to receive suggestions from friends while in the store and this technique has been proved to increase perceptions of social presence even though other people are only virtually present (Grewal et al. 2019). The next step suggested by Grewal et al. (2019) to provide convenience and social presence in the retail context is service robots because they are a kind of technology that creates social presence even in absence of human beings.

For all the reasons discussed above the beauty industry is an excellent fit for the implementation of service robots because not only they are in line with the technologies currently used in the industry, but they even overcome some important limitations of such devices through the elicitation of social presence. Indeed, customers in the market are becoming increasingly familiar with AI-powered recommendation systems in various forms and this is a good premise for acceptance of service robots (de Graaf & Ben Allouch, 2013). In addition to that, the increasing variety of products offered, which was proved to overwhelm novice consumers, can lead to uncomfortable instances in which novices are willing to avoid interactions with service employees to avoid embarrassing situations due to their lack of expertise in the make-up domain (Uzzi, 2019) and service robots represent a great solution in such occasions.

CHAPTER 2 - LITERATURE REVIEW

This work analyzes the interaction between six variables: customer knowledge of the product or service, anticipated embarrassment in the service encounter, robot anxiety, robot design and trust in robots' advice. In particular, the focus of this study concerns the effect of customer knowledge on trust in robots and the role of anticipated embarrassment, robot anxiety, and robot design in such process. These constructs are connected by prior literature's findings which suggest that they either hinder or foster trust in robots.

For instance, expertise in certain domains was proved by Logg, Minson and Moore (2019) to lead to discarding of algorithmic advice due to an effect called *algorithm aversion* (Dietvorst, Simmons, & Massey, 2015) due to *overconfidence* of experts. Several processes have been indicated as possible causes of this behavior such as *egocentric discounting (*Yaniv & Kleinberger, 2000), *insufficient adjusting* (Tversky & Kahneman, 1974), *egocentric bias* (Krueger, 2003) and *negativity bias* in advisor's reputation formation (Yaniv & Kleinberger, 2000). However, this effect has never been investigated in consumer contexts and in instances in which the source of the advice is a robot. This effect seems to indicate that experts in certain consumer contexts -thus consumers exhibiting high levels of customer knowledge– may be more prone to rely on service robot's advice.

Moreover, it makes sense to think that in consumer contexts, other cognitive and affective processes may be triggered and mediate such process. Miller (1996) proved that lack of customer knowledge can generate anticipated embarrassment. This is because it is likely to trigger the mental processes discussed in both *social evaluation theory* (Miller, 1996) and *dramaturgic theory* (Higuchi & Fukada, 2002) which construe two important antecedents of embarrassment and anticipated embarrassment.

However, the effect of mediation of embarrassment between the relation of customer knowledge and trust in robot advice is shaped by robot anxiety. Indeed, when people are afraid of robots, they are less likely to trust the robot and rely on its advice. This reasoning is based on the fact that prior literature on robot anxiety demonstrated that this fear causes human-robot interaction avoidance and it decreases trust in the robot (Nomura et al. 2006; de Graaf & Allouch, 2013; Mende et al. 2019; Mori, 1970; Mori, MacDorman, & Kageki, 2012; Mathur & Reichling, 2016)

It should be noted that robot design was proved to crucially shape robot anxiety. Indeed, the *uncanny valley effect* discovered by Mori (1970) predicts higher liking for anthropomorphized designs with respect to non anthropomorphized designs (Mori, 1970; Mori, MacDorman, & Kageki, 2012), however, when the robot looks almost perfectly like a human being, Mathur & Reichling (2016) demonstrated that people experience a sense of uncanniness and this effect influences trust in robot. Moreover, cuteness in robot design was expected to decrease perceived threat stemming from the robot (Nenkov & Scott, 2014; Caudwell, Lacey, & Sandoval, 2019) and thus decrease fear of the robot.

2.1 - CUSTOMER KNOWLEDGE

Alba and Hutcherson (1987) define customer knowledge as a construct made of two interrelated concepts namely familiarity and expertise. Familiarity refers to the number of product- or service-related experiences accumulated by the consumer (Alba & Hutcherson, 1987). According to the authors, such product-related experiences include exposure to advertising, information search, interactions with service employees and salespeople, product usage others. The authors define expertise as the ability of the customer to perform product- or service-related tasks successfully. It includes cognitive structures and processes required to perform product-related tasks effectively. There is a connection between these concepts, due to the fact that increased familiarity tends to result in increased expertise. Alba and Hutcherson (1987), identified five dimensions of expertise developed through the enhancement of customer familiarity with the service: cognitive effort, cognitive structure, analysis, elaboration, and memory. They demonstrated that increased familiarity leads to a reduced cognitive effort required for decision making, higher refinement in cognitive structures, greater ability to analyse product or service- related information, greater ability to elaborate given information generating accurate knowledge and, lastly, greater ability to remember product and service-related information. This means that customers with different levels of customer knowledge differ along several dimensions including the information and cognitive tools available for the decision-making process. Dagger and Sweeney (2007) recognize the effectiveness of using customer knowledge as a behavioural segmentation variable and distinguish between customers exhibiting low and high levels of customer knowledge referring to them as novices and experts (or novice and expert customers). According to them, this proves that experts and novices go through significantly different customer experiences and thus they may need to be treated differently by the service provider.

Differences in cognitive tools available for novices and experts are attributable the fact that domain expertise affects the way people process information and leads to different biases in the decision-making processes. Stanovich and West (2000) distinguish between two main ways of processing information, namely system 1 and system 2. Kahneman (2011) investigated differences in the way they work and argues that system 1 can be thought of as a way of processing information that takes little effort, occurs often automatically or with little voluntary control and operates quickly. system 1 can produce effortlessly feelings, impressions and intuitions that, if endorsed by system 2, can become the basis of explicit beliefs, deliberate decisions and voluntary actions. Most of the time, system 2 accepts the inputs of system 1. However, according to the author, when system 1 is not enough for a specific task, people activate system 2 to engage in more detailed or specific processing. System 2 (Stanovich & West, 2000) is a way of processing information through voluntary allocation of attention to perform effortful mental activities. These activities include complex calculations, conscious choices and decision-making that requires concentration. Kahneman (2011) states that system 2 can also change the way system 1 works by altering its automatic functions of attention and memory. Most of what people think is produced by system 1, however system 2 is mobilized for more difficult tasks and in general it has the last word. Indeed, system 2 is the only way to process things through comparison of several attributes and making active choices about options. However, it requires a higher investment in terms of energy and effort. In fact, Kahneman (2011) argues that system 1 processing does not allow to deal with multiple factors at the same time, but it has the advantage of working effortlessly. Moreover, as Stanovich & West (2000) point out, it allows people to establish simple relations and to integrate information about a specific topic as long as these are easy to process. This division of tasks is extremely useful according to Kahneman (2011) because it optimizes performance while minimizing effort. However, system 1 exposes people to biases, which are defined by the author as systematic errors or patterns of deviation from rationality in judgement. Biases reflect a subjective interpretation of the input that is being evaluated. They can lead to perceptual distortion, overconfidence and illogical or unfounded judgements. When people process information through system 1, they are more exposed to biases. According to Kahneman (2011), biases can only (but not always) be avoided when they are detected by system 2. The problem is that this is not always the case, and even awareness of the bias is not a sufficient condition for granting bias correction. This means that when biases occur and when they are not detected from system 2, people are not aware that they are making a decision based on wrong or unfounded intuitions, that they are underestimating a risk, that they are missing a bit of information or that they are overestimating their intuition. Because novices and experts differ concerning cognitive tools available (Alba & Hutcherson, 1987), when processing information they can be expected to follow different reasoning processes both in terms of system 1 and system 2. As a consequence, they can be expected to be exhibit different biases and to achieve different decision-making outcomes. Indeed, novices can be misled to focus their attention on not-so-relevant, easy to process information about products and services (such as brand familiarity or price) because they lack the cognitive structures they need to correctly integrate all the necessary information. On the other hand, experts -although they are skilled in integrating a greater amount of complex information- can be misled to overestimate their skills, overweight their intuitions and discard others' advice. This reasoning is supported by the finding that skilled individuals learn to rely on their intuitions because these allow for effortless, quick and (usually but not always) accurate decisions (Kahneman, 2011). According to the author, it is extremely difficult for expert individuals to recognize whether intuitive answers that come easily to mind are the result of a skill or of an unfounded heuristic. This means that experts, who are more likely to produce intuitive responses, are more likely to rely on their own intuition regardless of whether the information is the result of an expertise or an instinctive and biased response of system 1 (Kahneman, 2011).

Another interesting consequence of expertise discovered by Kahneman (2011) is that it increases efficiency of decision making. The author proved that brain activity associated with a task changes as people become skilled in that task. More specifically, as people become more familiar with a specific task, the energy needed for the task diminishes and fewer brain areas are activated. As a consequence, experts refining a skill are able to perform it effectively investing very little energy in it and experiencing cognitive ease. On the other hand, novices, who have not developed such a process, must effortlessly make decisions about elements they are not familiar with and this can lead to cognitive strain according to Kahneman (2011). The author argues that a common way to avoid cognitive strain is relying on more linear decision-making processes using rules of thumbs or relying on easy-to-process information. An important implication of cognitive ease and strain shown in the publication is that while cognitive ease reinforces people's trust in their own intuitions, cognitive strain provokes a feeling of discomfort. Because experts are more likely to experience cognitive ease, they are more likely to rely on their own intuitions and this can eventually lead to overconfidence. On the other hand, novices are more likely to experience cognitive strain due to their lack of knowledge about the product or service and thus they are more exposed to discomfort caused by cognitive strain. People experiencing this kind of discomfort often feels the need to address this negative feeling and this compels them to engage in coping behaviours to reduce cognitive demand. As a consequence, novices are more tempted to simplify the decision-making process and rely on others' advice because these strategies allow them to reduce cognitive effort. Another important effect of cognitive strain is that it makes people lose touch with their intuition and it increases gullibility i.e. the tendency to be easily persuaded by external sources (Kahneman, 2011).

Interestingly, not only cognitive processes undergone by novices and experts are different, but so are also biases, heuristics and approaches to decision making. Concerning approaches to decision making, Alba and Hutcherson (1987) have analysed how differences between service and/or product knowledge affect motivation, attitude formation, decision making processes, behaviour and more. In addition to that, concerning differences in decision-making approaches and service evaluation, Park and Lessing (1981) analysed how decision making differs in customers with low, moderate and high product familiarity along the dimensions of perceptual category breadth, decision time, confidence in choice and use of heuristic. Use of heuristic involves reliance on shortcuts for facilitating decision-making. In other words, it refers to a mental short cut that allows people to substitute a difficult question they have trouble addressing with a simpler one (Kahneman, 2011). This procedure allows for the achievement of adequate, although often imperfect solutions to complex problems. Park and Lessing's (1981) findings are consistent with the reasoning that limited product or service familiarity can have a similar effect to cognitive limitation. In fact, just like cognitive limitation, lack of familiarity leads to a tendency to ignore or discount important information and use more linear decision-making processes to simplify a complex decision task (Park & Lessing, 1981; Alba & Hutcherson, 1987). The reason for this effect according to Alba and Hutcherson (1987) is that lack of familiarity lowers comprehension and increases required cognitive effort. As a consequence, customers that experience these limitations develop a higher tendency to make use of mental shortcuts to make a decision (Alba & Hutcherson, 1987).

It should be noted that experts are not strangers to mental shortcuts either (Park & Lessing, 1981). However, the ones used by experts are different with respect to the ones used by novices because they have been refined through skills and practice[3]. As a consequence, another important difference between experts and novices is the formers' superior efficacy in decision making as well as in mental shortcut use according to Park and Lessing (1981). This happens because mental shortcuts used by novices are driven by a need to simplify a decision making overly complex for their vague knowledge in a specific domain to decrease cognitive strain (Kahneman, 2011). Per contra, heuristics used by experts are driven by (and improved through) repetitiveness in the task. For this reason, mental shortcuts used by experts and novices differ significantly both in terms of structures, attributes considered, confidence in the decision-making outcome but, most importantly, they differ in terms of efficacy of decision making (Park & Lessing, 1981). According to the authors, novices are more likely than experts to rely on a more linear decision-making process based on signalling attributes like price and familiar brands because they are not able to understand complex attributes affecting qualities. This process is the result the availability heuristic which was identified by Tversky and Kahneman (1974) and it is a bias of system 1, that misleads people to rely on examples or information that more easily come to mind. According to the authors, when people incur in availability bias, they overestimate the relevance and importance of information that easily comes to mind at the expense of information that requires greater effort for being processed. Thus novices, who are not able to easily integrate complex attributes in their decision making, are more likely to base their decision process on more simple characteristics that they easily comprehend (e.g. price or brand familiarity) because these qualities are readily available in their minds. There are some instances in which experts rely on signalling attributes like price and brand familiarity according to Park and Lessing (1981). However, the authors proved that they are less likely to be confident in a decision-making process that is solely based on such dimensions. Indeed, their ability to integrate in their decision other functional attributes (which are more diagnostic with respect to signalling attributes), causes a tendency in experts to rely on more complex decision-making processes (Park & Lessing, 1981). However, as expertise increases and as the purchase and decision-making task becomes more repetitive, the decision time decreases, and the process becomes a sort of automation or routine that does not require the expert to actively think about it (Kahneman, 2011). Another important difference concerns the extent to which experts and novices tend to be confident in their decision-making outcome according to Park and Lessing (1981). Indeed, in general experts tend to be more confident with respect to novices concerning the outcome of their evaluation (Park & Lessing, 1981). To encapsulate findings about superior efficacy of decision making and use mental shortcuts by experts: novices tend to simplify decision making due to lack of understanding of the domain, they tend to ignore information they do not comprehend due to availability bias. This makes them more confident with respect to experts in a decision-making outcome that only takes into consideration signalling attributes. However, in general experts tend to be more confident in their decisions with respect to novices. This happens because the experts developed a more effective and efficient method for optimize decision making and take

[3] This comes from a long tradition of studies which has its roots in Chase and Simon's (1973) studies of expert intuitions developed through the study of recognition and memory of experts and how they change as a function of expertise in the chess domain.

into consideration a wider variety of elements in their decision making. In addition to that, as the task becomes repetitive for an expert it requires him little time and attention with respect to novices. All these elements have important implications on advice taking because it indicates that experts and novices can be expected to exhibit different levels of confidence in their judgement and this influences the extent to which they are willing to seek for and comply with advice (Park & Lessing, 1981). Moreover, this suggests that because experts and novices go through different decision-making processes and produce different outcomes, their customer journey should be different to cater the needs of both groups.

In a research conducted by Mittal, Kumar and Tsiros (1999), the authors empirically proved how decision-making changes as expertise is acquired through the analysis of how relationships among attribute level evaluations, service satisfaction and behavioural intentions toward manufacturer and service provider in the automotive sector change over time. This allowed them to demonstrate that the relationship between attribute-level evaluations and satisfaction is dynamic and changes as customers become experts in a specific domain. Moreover, the showed that weights of attributes, and thus given importance of each attribute, change over time. In other worlds, as customer knowledge of the service or product progresses, different factors are taken into account when it comes to service evaluation. This also has an effect on customer satisfaction and behavioural intentions according to the author. These results imply that experts and novices differ in the extent to which they are satisfied with the service or product, but also in the elements they use to evaluate it. This is a result of the progressive development of more sophisticated cognitive tools (Alba & Hutcherson, 1987) and of the decision-making process (Park & Lessing, 1981). Because of this phenomenon, the effect that an attribute has on service evaluation changes as the consumer gains familiarity and expertise with the service. This also influences customer satisfaction and brand patronage (Mittal, Kumar & Tsiros, 1999).

They way attribute importance changes or shifts over time has been investigated by many authors who have used various classifications from different models to investigate how novices and experts weighted different classes of attributes. For instance, Bettman and Park (1980), Brucks (1985) Rao and Monroe (1988) and Devlin (2011) used the functional/non-functional distinction and demonstrated that objective expertise with the product or service positively correlates with attached importance to functional cues at the expense of non-functional cues in several purchase and service contexts. They showed that as customer expertise grows customers tend to give more importance to functional attributes and less importance to non-functional attributes (Bettman & Park, 1980; Brucks, 1985; Rao & Monroe, 1988; Devlin, 2011).

Dagger and Sweeney (2007) applied the search, experience and credence model classification of attributes proposed by Nelson (1970) to determine how service knowledge affected attributes weight according to the model's categorization. According to Nelson (1970) search attributes are defined as features of a product or service that can be assessed before the purchase, experience attributes are qualities that can only be assessed after purchase, and credence attributes are difficult to assess even after purchase. Starting from this classification, the expriments conducted by Dagger and Sweeney (2007) demonstrated that novices attached greater importance to search attributes, experts attached greater importance to credence attributes, while both types of customers attached a certain importance to experience attributes. According to the authors, the explanation of this phenomenon lies in the fact that search attributes are easier to assess and understand with respect to credence attributes. Therefore, even customers exhibiting low levels of product or service knowledge are able to discern and assess search attributes. Because these attributes are more readily available with respect to credence attributes, novices are more likely to rely on them. However, as customers develop their expertise and familiarity with the service or product, they become able to evaluate more complex attributes (credence attributes). Because these attributes are more diagnostic with respect to search attributes, greater importance is attached to credence attributes as customers become experts. Interestingly, the studies confirmed that there is one experience attribute that was considered to have the same importance by both novices and experts: service interaction. This construct is defined as the communications and manner of interaction between the customer and the service provider (Dagger & Sweeney, 2007). The fact that this dimension plays such a crucial role in the service and product evaluation of both novices and experts suggests that it should be handled and conceived very carefully.

Although novices and experts place almost the same importance to the service interaction in the evaluation of the service, their preferences in the context of interactions with recommendation systems are extremely different according to Knijnenburg, Reijmer, & Willemsen (2011). Indeed, they empirically demonstrated that experts prefer systems that allow them to customize autonomously the service or product and that allow them to independently sort offerings according to how each offering scored on different attributes that were considered more relevant by the expert customer. On the other hand, novices prefer systems that sort offerings based on more linear evaluations such as the most often purchased offerings by other users. This is in line with the consideration of Dagger and Sweeney (2007) that lower service or product knowledge constrain novices' ability to process higher order characteristics. Moreover, this finding confirms the forecast by Alba and Hutcherson (1987) that novices are more likely to rely on other consumers' opinion to overcome their lack of knowledge with respect to experts. In addition to that, these results suggest that novices are more prone to rely on advice of others because they recognize their lack of expertise in the service or product domain.

The effect of customer knowledge on advice taking (and discounting) and confidence in decision making was further analysed by Logg, Minson and Moore (2019). In various studies they confirmed that novices and experts exhibited significantly different levels when tested for these two elements in the specific context of algorithm appreciation. They define algorithm appreciation as the extent to which people prefer algorithmic advice to human advice and it was demonstrated to be moderated by knowledge in the subject matter of the decision-making process. By preference for a certain type of advice Logg, Minson and Moore (2019) refer to the extent to which advice from different sources (human or algorithmic) is integrated in decision making. The authors discovered that, in absolute terms, novices discount algorithmic advice less than experts do. That is, when advice on a certain decision comes from an algorithm, novices are more likely than experts to adjust their opinion to the advice. Experts discount more both human and algorithmic advice with respect to novices but, in relative terms, they discount human advice more with respect to algorithmic advice. In other worlds novices are more likely to rely on advice regardless of its source (human or algorithmic) with respect to experts. Both experts and novices tend to rely more on algorithmic advice than on human advice, however, experts tend to discard both human and algorithmic advice (Logg, Minson & Moore, 2019). This is consistent with Alba and Hutcherson's (1987) findings. In general, the higher advice discounting by experts is explained by Logg, Minson and Moore (2019) as the result of an overconfidence bias. Thus, experts have a tendency to weight more their own opinion with respect to others' opinion regardless of its source.

According to Healy and Moore (2007) there are three main kinds of overconfidence. The first kind of overconfidence is also termed *overestimation* and it is described by the authors as the overestimation of the individual's abilities, control, performance, and level of success. The second kind of overconfidence is also called *overplacement* and it refers to instances in which an individual believes to be better than the others or better than the median of the population under analysis. The third kind of overconfidence is also referred to as *overprecision* and it regards instances in which individuals hold excessive certainty in the accuracy of their beliefs. The underlying cause of decision-makers' general overconfidence according to Healy and Moore (2007) is imperfect knowledge of the individuals' actual performance, skills, and expertise, combined with even scarcer knowledge of other people's actual performance, skills and expertise. An interesting effect discovered by Healy and Moore (2007) is that as task difficulty increases, overestimation increases while overplacement decreases. This means that people facing a difficult task have a tendency to believe that they are performing better than what they actually are. However, their bias to believe that they are outperforming others decreases and in fact tend to believe that they are worse than others in that task. This leads to higher opinion of advisors and to increased reliance on others' advice (Healy & Moore, 2007). This finding seems to suggest that novices, who are more likely than experts to find a task difficult, have a tendency to believe that other people know or do better than them. Experts on the other hand, are more prone to discount advice, but while exhibit a tendency to simply discount other people's estimates, they sometime perceive algorithmic advice as a tool to adjust their own estimate/ decision (Logg, Minson & Moore, 2019). Therefore, they are more likely to adjust their estimates including algorithmic advice rather than human advice (Logg, Minson & Moore, 2019).

However, findings about algorithm appreciation are contradicting. Indeed, Dietvorst, Simmons, & Massey, (2015) showed that people tend to have lower tolerance for algorithmic mistake than for human mistake after seeing both humans and algorithms err. The authors suggest that witnessing algorithm making mistakes triggers algorithm aversion i.e. the tendency to discard algorithmic advice. The finding that experts are more prone to exhibit algorithm aversion than novices is the unifying concept on which both algorithm aversion theory (Dietvorst, Simmons, & Massey, 2015) and algorithm appreciation theory (Logg, Minson & Moore, 2019) agree. An overall algorithm appreciation can be observed when people are not able to detect the error or if the error is not directly imputable to the algorithm (Dietvorst, Simmons, & Massey, 2015; Logg, Minson & Moore, 2019). In this sense, an explanation for novices' higher algorithm appreciation (and lower algorithm aversion) lies in the fact that novices are less able than experts to detect errors or to acknowledge that the mistake was caused solely by the algorithm. These considerations are extremely relevant because there is evidence of the fact that algorithmic advice can be more accurate than human advice and could be extremely useful in helping novices overcoming their lack of knowledge (Dawes, 1979; Dawes, Faust & Meehl, 1989; Yeomans et al. 2019). Moreover, it could be argued that objective mistakes in the field of shopping recommendation are less objectively detectable and thus it could be a context in which algorithm aversion is naturally lower.

To summarize, for what concerns the cognitive processes that novices and experts undergo when it comes to service evaluation, they differ on several dimensions. This has significant effects on repurchase intention and overall behavioural outcomes in the service encounter context. Among the most important differences we can identify disparities in: ability to perform task-related activities, cognitive tools available for decision making, cognitive biases, the decision making process in terms of both efficacy and efficiency, inputs used in the decision making process, relative weight assigned to each input, preference for interaction methods, the extent to which they rely on advice and confidence in the decision outcome.

It is then crucial for companies to understand and address such differences in order to more accurately serve the different needs of both kinds of customers. It is also important that companies recognize that preferences, cognitive and emotional states are dynamic and change over time as a function of customer knowledge (Dagger & Sweeney, 2007). They thus require a flexible and tailored approach aimed at following the customer as he develops a deeper knowledge of the product or service. Companies failing to do so run the risk to underperform in terms of customer satisfaction and patronage as well as customer relationship management according to the authors. Moreover, they risk incurring in misallocation of resources (Dagger & Sweeney, 2007).

2.2- EMBARRASSMENT

Because customers with diverse levels of customer knowledge go through different decision-making processes, they can also be expected to go through different affective responses due to differential levels of confidence experienced during the service encounter. Indeed, awareness of their lack of knowledge concerning the service encounter, its script or product characteristics could elicit a feeling of discomfort in novices due to embarrassment. Indeed, Miller (1996) demonstrated that previous experience with a certain event negatively correlates with perceived and anticipated embarrassment. Moreover, the fact that novices may find more difficulties in formulating specific questions because of their lack of service or product knowledge, can enhance this sense of embarrassment (Alba & Hutcherson 1987).

According to Grace (2007), embarrassment has often been analysed as connected to humiliation and shame. However, the scholar argues that in the context of service encounter, a distinction between these concepts is more appropriate. Indeed, humiliation is defined as the enforced social lowering of an individual or group of individuals and the process of annihilation of their pride, honour, and dignity (Linder, 2001). It is unlikely to occur in the service context, exception made for some very extreme cases (Grace, 2007). Shame on the other hand, shares more commonalities with embarrassment because they both concern a feeling of discomfort stemming from negative evaluations of the individual's self (Grace, 2007). However, according to Grace (2007), they differ in the extent to which shame concerns a perceived frailty of one's core self while the threat in embarrassment affects to one's presented self. In other worlds shame and embarrassment are both related to a negative projection of the individual's self. Their difference lies in the fact that while an individual who is experiencing shame is concerned with his own negative opinion of himself, an individual who is experiencing embarrassment is concerned with the negative opinion of others of his self (Grace, 2007). For this reason, Grace (2007) suggests that the presence of others and their behaviour plays a crucial role in the embarrassment process while they are much less relevant in the shame process. These emotional states are not mutually exclusive and can even happen simultaneously, however embarrassment and its management are more relevant in the service encounter because it is more easily addressable by the service provider (Grace, 2007). Moreover it is essential for service providers to take care of this aspect because embarrassment was demonstrated to have a negative effect on the customer experience but also on satisfaction with the purchase, intention to repurchase the product or service and even word of mouth after the purchase (Dahl, Manchanda & Argo, 2001).

Embarrassment was first investigated as a distinct concept by Edelmann (1981). He defined it as an uncomfortable psychological state associated with the violation of expectations that regulate and establish desirable behaviour. More specifically, it is defined as a feeling of concern for an individual's public image and the reactions from others (either real or imaginary) to inappropriate behaviour. For instance, in the context of a service encounter, inappropriate behaviour refers to noncompliance to usual roles, actions and jargon used within the so-called service script. Thus, the presence of other people (whether real or imagined) plays a critical role in the arousal of embarrassment . Indeed, this psychological state is provoked by a perceived threat to an individual's presented self, stemming from negative evaluations of real or imagined audiences (Edelmann, 1981). Consequently, presence of other people and the interaction with them can trigger embarrassment and awkwardness because this can elicit thoughts that one is being evaluated (Edelmann, 1981).

According to Miller (1996) and Higuchi and Fukada (2002), two main theories explain embarrassment: *social evaluation theory* and *dramaturgic theory*. *Social evaluation theory* claims that for an individual to experience embarrassment, his self-esteem must be eroded due to the perception of negative evaluation that others may formulate about the individual (Miller, 1996). In other words, for people to experience embarrassment the usual image that they portray of their self must be at stake. *Dramaturgic theory* models indicate, as a factor triggering embarrassment, the disruption of social performance (Higuchi & Fukada, 2002). In the context of service encounter, disruption of social performance entails inability to carry out customer's role in the service scripts. For instance, lack of knowledge about common practices during the service encounter or simply the inability to formulate questions for lack of knowledge of technical jargon can trigger embarrassment (Higuchi & Fukada, 2002). For this reason, novices, who generally are unfamiliar with the service or product, tend to be less confident about their ability to perform their role in the service script and, as a consequence, they feel higher discomfort in the service encounter interaction (Higuchi & Fukada, 2002). Moreover, this anticipation of inability is likely to trigger concerns about their portrayed self and lead to embarrassment (Higuchi & Fukada, 2002).

Familiarity with product and purchase process was demonstrated by Dahl, Manchanda and Argo (2001) to reduce the amount of uncertainty and thus embarrassment provoked. According to the authors, this happens because as familiarity with service encounter increases, consumers become more confident in their ability to correctly perform their role in the service script. In addition to that, expertise and familiarity enhance customers' ability to predict the reaction of the service provider and of other customers. Interestingly, this also leads to an increase in the perception of the customer's ability to make an effective decision concerning the purchase. On the other hand, unfamiliarity with the service encounter can increase the perception of complexity associated with the task because the customer is not able to predict how the service encounter will unfold. As a result, the authors demonstrated that the very same task can be perceived as highly complex by novices but extremely simple -even part of a routine- by experts. The combination of lack of familiarity with the product or service and perceptions of complexity associated with the purchase was demonstrated to make social presence of other customers more salient. Because social presence of others can trigger the fear of negative evaluations of the portrayed self, this can aggravate the feeling of embarrassment (Dahl, Manchanda & Argo, 2001). Thus, novices, as opposed to experts, can be expected to be more likely to experience embarrassment.

Interestingly, a study conducted by Baumeister et al. (2001) demonstrated that negative emotional states, feedback, and information is processed more thoroughly than positive ones and for this reason they are more effective in shaping behavioural responses. Moreover, bad impressions are formed more quickly, and they are hold for longer in people's minds with respect to positive ones. In addition to this, they provided an empirical evidence of the fact that individuals are more motivated to avoid bad self-definitions than to achieve positive ones. In other words, people are more compelled to protect the usual image they portray of themselves than to enhance it (Baumeister et al. 2001). According to Kahneman (2011) this tendency is the result of an affective form of loss aversion. In cognitive psychology loss aversion indicates the tendency of people to weight and compensate more for losses than for gains (Kahneman, 2011). This means that anticipated embarrassment can be expected to be extremely influential over people's behaviour because it threatens what people perceive as their reference point in terms of the image they hold about their self.

A further study concerning embarrassment in the service encounter context was conducted by Grace (2007) and it focused on the antecedents and consequences of this emotional state from an emotional, psychological and behavioural point of view. Sources of the embarrassment were divided by the author in "self", "service provider" and "others" -to be intended as other people-. Stimuli were classified in six categories namely criticism, awkward acts, image appropriateness, forgetfulness/ lack of knowledge / error, environment/ surroundings and lastly violation of privacy. Interestingly, the most common stimulus that occurred in the study when the source was the customer was forgetfulness / lack of knowledge / error, while the most common stimulus that occurred when the source was the service provider was criticism (thus audience's negative evaluation). These findings are in line with both *Dramaturgic* (Higuchi & Fukada, 2002) and *Social Evaluation* (Miller, 1996) theories because they confirm that among the most common fears triggering embarrassment there are concerns about ones' prostrated self-image as well as fear to make mistakes that disrupt social performance (Grace, 2007). Furthermore, this confirms the importance of lack of knowledge and others' evaluations as a primary source of embarrassment. For what concerns the behavioural reactions, the most common one in the study was leaving the store. Moreover, 73% of participants in the study claimed that they did not want to return to the store in the future, that they would have avoided it in the future or that they would have only gone back because of lack of alternatives. For what concerns word of mouth, 61% of participants told others about their negative experience and 55% of participants told them not to engage with that service provider. The author identifies this phenomenon to be a very serious matter for service providers, and as such it should be addressed carefully. Another extremely interesting insight is that in the majority of embarrassing situations (66% of respondents in the study claimed so) are triggered by the service provider. This indicates that there is room for improvement for service providers' management of customer embarrassment (Grace, 2007).

Anticipation of embarrassment can be further enhanced by a phenomenon that Gilovich and Savitsky (1999) defined as the *spotlight effect* which is the tendency of people to hold egocentrically biased beliefs. In other words, people overestimate how salient their appearance and behaviours actually are to other people. The authors showed that people making an embarrassing mistake tend to believe that other people present have noticed it when they have not. This also holds for inner emotional states such as disgust or nervousness. This effect amplifies perceived embarrassment because it triggers the false impression (or the exaggerated impression) that other people are negatively evaluating the individual. Gilovich and Savitsky (1999) propose an explanation for such phenomenon based on anchoring and adjustment. When people try to estimate how negatively they are being evaluated by other people, they use their own negative judgement as an anchor. The authors claim that individuals often condemn themselves more harshly with respect to how harshly they are judged by other people. Even when an individual recognizes that and tries to adjust his estimate accordingly, the adjustments that he makes from his anchoring point (which is his own self negative evaluation) are usually not sufficient and this causes an overestimation of the negative opinion that others have of the individual. As a consequence, when it comes to forecasting how harshly an individual will be judged and how much people will notice an embarrassing situation in which the individual is involved, there is a significant difference between individuals expectations and actual evaluations of other people. This reinforce the concerns for ones' portrayed image, and it increases the effect of both anticipated and perceived embarrassment (Gilovich & Savitsky, 1999).

Embarrassment can then become a serious obstacle to the establishment of a solid and loyal customer base. Indeed, embarrassment can undermine the process of customer knowledge accumulation because of the discomfort experienced during the service encounter. Such discomfort could lead to a desire to terminate the relationship with the service provider to prevent future embarrassment. Novices are more likely to experience embarrassment and interaction with other people can become a further source of stress. Indeed, social interactions with the service provider or with other customers can aggravate this feeling if the customer believes that other people could negatively judge him. It is vital for companies to manage service encounter carefully to reduce the occurrence of this emotional state, especially in interactions with novices as they are more vulnerable to this feeling.

Providing customers with the possibility to avoid human social interaction through the use of Technology Based Self-Service (TBSS) can prevent the occurrence of embarrassment in novices according to Londono, Davies and Elms (2017). TBSS allows customers to receive all the information they need about products and services without feeling judged for their lack of knowledge. Indeed, because the occurrence of embarrassment requires customers to be concerned about the negative evaluations of other people, the authors proved that interacting with an inanimate object neutralizes, or at least reduces, embarrassment. In this context, the use of service robots could provide a solution especially for companies that want to establish a relationship with their customers but that also want to prevent their customers from experiencing discomfort during interactions. Indeed, according to a study conducted in the service robot context, specifically where robots were used as guides in museums and shopping malls, consumers particularly appreciated the fact that robots treated everyone in the same way and did not make them feel judged (Sabelli & Kanda, 2015).

2.3 - ROBOT ANXIETY

A major problem facing the adoption of service robots and the extent to which customers trust them is robot anxiety (de Graaf & Allouch, 2013). This concept is usually defined by the authors as user's anxious or negative emotional reaction triggered by both real and imagined HRI. Robot anxiety is also referred to as robot fear or fear of the robot and it negatively affects perception of control over the situation because it decreases perceptions of predictability of robot behaviour (de Graaf & Allouch, 2013). Nomura et al. (2006) developed a robot anxiety scale and claimed that the two psychological determinants of robot anxiety are general anxiety towards technological products (also known as technophobia) and communication apprehension. Technophobia refers to the phenomenon that occurs when a certain technology triggers fear or stress in individuals (Brosnan, 2002). Communication apprehension is defined as a feeling of anxiety or fear caused by a real or anticipated communication with another agent (Nomura et al. 2006). It is a form of social anxiety triggered by a perception of loss of control over the interaction. This loss of control is caused by unpredictability of the other agent. In fact, because most people are not familiar with robots, they tend to be less confident in their ability to predict robot behaviour (Nomura et al. 2006). Robot anxiety prevents individuals from comfortably interacting with robots thus leading to avoidance of interaction with such unfamiliar agents (Nomura et al. 2006). Ivaldi et al (2016) proposed that seemingly unrelated events such as trends in literature and sci-fi films could have affected and enhanced fear of robots especially in technophobic people. Their study also proved that people experiencing robot fear behave differently in HRI, talking less to the robot and avoiding looking at it. Mende et al. (2019) suggested that HRI can trigger service robot anxiety and this fear tends to have huge negative effects on customer loyalty and service satisfaction. Therefore, companies should track consumers responses to HRIs and assess customer readiness and willingness to interact with robots before exposing them to service robots (Mende et al. 2019). Another reason concerning negative attitudes towards robots was suggested by Waytz and Norton (2014) and it relates to concerns for job threats and replacement of human labour associated with the phenomenon of botsourcing (replacement of human labour with robot labour). According to Mende et al. (2019) another reason for this discomfort can be attributed to associations to threat to human identity and scenarios in which artificial intelligence slips out of human control.

Mende et al. (2019) investigated compensatory behaviours that people engage in to cope with the discomfort caused by robot fear. They showed that the interaction with service robots induces a sense of discomfort in people which results in compensatory behaviours. These compensatory behaviours can take the form of compensatory consumption in terms of indulgent food consumption and preference for luxurious products. However, this effect is reduced when food provided is perceived as healthy, when consumers perceive a high degree of social belonginess and when the robot does not have strongly human-like features. This study suggests that mechanizing the robot, i.e. designing it in such a way that it does not possess strong human-like characteristics, attenuates discomfort perceived in HRIs when robot anxiety is high (Mende et al. 2019).

Although there is disagreement concerning the effects of designing robots with human- or machine-like appearances, it seems clear that design plays a key role in the elicitation of discomfort that reduces trust in robots.

One of the first studies conducted on robot anxiety discovered an effect called the *uncanny valley law,* which predicts that human beings perceive a sense of uncanniness in HRIs which is exacerbated when the robot looks extremely similar to but not perfectly like a human being (Mori, 1970; Mori, MacDorman, & Kageki, 2012). In other words, imperfect human likeliness was proved to cause dislike in participants of various experiments. The uncanny valley effect was empirically tested by Mathur and Reichling (2016) who demonstrated that it influences not only conscious assessment of robots, but also participants' subconscious decisions concerning robots' trustworthiness. Participants in their study were exposed to pictures of the faces of 80 existing robots and were asked to rate them on a continuum from highly mechanical to highly human-like. The results showed that as robots move towards a more human-like appearance, people find them more likeable and trustworthy. However, likeability decreases abruptly for robots that look almost like but not perfectly as human beings (Mathur & Reichling, 2016). This effect was demonstrated to have a an impact on the degree of trust afforded to robots in an investment game conducted in the experiment. Discomfort caused by the *uncanny valley effect* had important implications on trust in robots decreasing the extent to which participants in the experiments trusted different robots (Mathur & Reichling, 2016). The *uncanny valley law* shows an important connection between robot anxiety or fear and robot design, in particular, it suggests that robot design can moderate fear of robots.

A proposed explanation for such discomfort is the association to corpses and a natural repulsion towards them for evolutionary reasons (Broadbent, 2017). According to the author, the *uncanny valley effect* is the result of a disease avoidance mechanism to prevent infections from diseased or dead bodies. Another reason concerns conflicting cues that humans receive from robots. Indeed, these cause category confusion and a violation of behavioural expectations. In other words, Broadbent (2017) argues that people associate human-like appearance of the robot to human-like characteristics. As a consequence, people associate robots to human beings, and they expect them to behave as such. When robots inevitably fail to do so, people perceive a mismatch between the anticipated human-like characteristics and their actual imperfect non-human-like qualities. This violation of expectation causes a category confusion which eventually provokes a sense of discomfort (Broadbent, 2017). MacDorman (2005) applied terror management theory on reactions to robots and proposed that the reason why robots produce discomfort in human being is related to the fact that they make mortality more salient by violating norms of human appearance and movement.

2.4 - ROBOT DESIGN

Careful design considerations can create associations that lead to lower levels of service robot anxiety and consequently affect reactions to HRIs and trust in robots (Broadbent, 2017). Caudwell, Lacey and Sandoval, (2019) demonstrated that robot design affects cognitive and emotional responses to HRIs, facilitating the establishment of relationships that are crucial for certain tasks' performance. These analyses are essential for a deeper understanding about behavioural responses to robots (Broadbent, 2017). Indeed, because the scope of service robot is highly social in nature, it is important for them to be designed and conceived in a way that fosters HRI instead of undermining it (Broadbent, 2017). It should be noted that conflicting findings have been identified regarding optimal design for different tasks. This suggests that different service robots' roles call for different designs. Several studies have been conducted to determine how design can be perfectly matched with the needs of people interacting with service robots. In particular, three main dimensions seem to affect human reactions to HRIs: physical embodiment, anthropomorphism and cuteness. These should be carefully considered when selecting the optimal design for a certain audience, task, or context.

2.4.1 -Physical embodiement

Physical and nonphysical AI agents elicit different reactions and perceptions of presence during HRIs (Caudwell, Lacey, & Sandoval, 2019). Indeed, cognitive, and social sciences recognize physical embodiment to be crucial for the production of social cues (Caudwell, Lacey, & Sandoval, 2019). An alternative solution to service robot is provided by digital virtual assistants or virtual agents (Wirtz et al., 2018). These are software interfaces without physical embodiment, that provide customized support and information to customers who want to avoid social interactions with service employees (Wirtz et al., 2018). Indeed, for customers experiencing robot anxiety and related discomfort and fear caused by HRIs, digital virtual assistants could be the optimal solutions. The lack of physical body usually decreases the perception of threat caused by the robot. This is because, without a physical body, the agent is intrinsically harmless (de Graaf & Allouch,2013; Mende et al. 2019). Moreover, consumers are already familiar with digital assistants and virtual images, and, for this reason, they may be more willing to accept virtual assistant advice if they fear robots. However, when participants of various studies did not experience excessive levels of robot anxiety, preference shifted towards physically embodied agents. For example, Reich and Eyssel (2013) demonstrated that people experiencing chronic loneliness are motivated to neglect robot anxiety and tend to prefer physically embodied social agents. It is then clear that anthropomorphism, and specifically one of its psychological determinants (chronic loneliness also referred to as sociality motivation), have an important effect on preferences concerning physical embodiment of the robot. In a study conducted by Wainer et al. (2006) participants rated a robot physically present, a simulated one on a computer screen and a robot shown through teleconferencing along a series of variables. The majority of people rated the physically present robot as more enjoyable and watchful as compared to the other two (Wainer et al. 2006). Social presence also plays a crucial role in social robots used for therapy (for example providing assistance to patients on a diet) because patients tend to form a stronger therapeutic alliance, sympathize and bond more with robots physically present as opposed to virtual agents (Kidd & Breazeal, 2008). Another study that showed that physical presence affects behaviour change was conducted by Mann et al. (2015) and it established higher compliance to instructions given by a robot than by a computer with the very same voice. Moreover, participants of the study were more willing to interact again with the robot than with the virtual agent. However, it should be considered that robot anxiety is a widely spread concern around people and that it can have an enormous impact on service robot acceptance and trust (Nomura et al. 2006). For this reason, it is important to assess whether customers are likely or not to exhibit robot anxiety.

Another interesting note concerns the perception of warmth and competence. In fact, service robots currently face some limitations in the extent to which they can replicate human emotions. This affects the perceived warmth of robots (Ivaldi et al, 2016). Warmth refers to the ability of the robot to convey friendliness, trustworthiness, morality, sincerity and helpfulness and it is a strong determinant of trust (Demeure, Niewiadomski & Pelachaud, 2011). To avoid this problem robots with cute design focused on eliciting a positive affect through the association with children (Nenkov, & Scott, 2014). This choice comes at the expense of perceived competence because the association with extremely naïve creatures decreases people perceptions of robots' competence (Demeure, Niewiadomski & Pelachaud, 2011). Indeed, competence was defined as a series of traits that relate to intelligence, creativity, perceived ability, skill, and efficacy and it is usually perceived to be higher in adult human beings than in infant human beings (Demeure, Niewiadomski & Pelachaud, 2011). This is in line with Fiske, Cuddy and Glick's (2007) Stereotype Content Model which predicts that certain association can lead to a trade-off in perceptions of these two dimensions of social cognition. Virtual agents could potentially overcome this problem because reproducing human emotions is more feasible through screen-based graphic than on a physical robot (Demeure, Niewiadomski & Pelachaud, 2011). In fact, virtual agents are not bounded to create associations to infants to elicit a perception of warmth. They can do so simply reproducing adult human beings' facial expressions or body language on a screen (Niewiadomski, Demeure & Pelachaud, 2010). Consequently, by using the image or voices of adult human beings, they can trigger associations to much more competent individuals. Warmth-competence perceptions are extremely impactful on trust in agent advice (both robotic and virtual) and, for this reason, they should be taken into consideration for optimal design selection of agents in various contexts (Niewiadomski, Demeure & Pelachaud, 2010).

2.4.2- Anthropomorphism

Anthropomorphism refers to the process of inductive inference that concerns the attribution of qualities that are in general specifically distinctive of human beings to non-human agents (Waytz, Heafner, & Epley, 2014). Examples of these characteristics are possessing a human-like mind or the ability to reason in a human-like way, as well as the ability to have feelings and agency (Waytz, Heafner, & Epley, 2014). De Graaf and Allouch (2013) demonstrated that anthropomorphism increases trust in robots, and it moderates robot anxiety, attitudes towards robots and intention to use robots. Three forms of anthropomorphizing have been identified by Aggarwal and McGill (2007): partial, literal, and accidental. Partial Anthropomorphizing refers to instances in which people attribute some human characteristics to non-human agents but recognize the entity as whole as non-human. An example is when consumers attribute a personality to a brand using a typical human schema (personality) for an inanimate object. Literal anthropomorphizing occurs when people mistake a non-human agent for a human agent as a result of an erroneous perception (for instance when people in the darkness mistake an object like stacked garbage bags for a human being). Accidental anthropomorphizing occurs when people identify some human characteristics in non-human agents and consider such outcome to be coincidental (for example when people see a person's face in a cloud) (Aggarwal & McGill, 2007). Moreover, people do not anthropomorphize objects with the same ease, both because of the nature of the object (Broadbent, 2017) itself and because of some psychological determinants described in the three-factor theory anthropomorphism (Epley, Waytz & Cacioppo, 2007).

Indeed, for what concerns the nature of the object, according to Broadbent (2017), people's tendency to anthropomorphize increases with the human likeliness of the object. The author mentions some important factors affecting human likeliness such as movement and shapes similar to the human body or face. Other features that foster anthropomorphism are sounds, voices and interacting in a human-like manner. Consequently, designing robots with human like features increases the possibility that people will associate them to humans. Broadbent (2017) proposes that this phenomenon can elicit diverse reactions and shape people's evaluation of the robot. Indeed, the author argues that anthropomorphism can lead to two outcomes. On one hand, it can facilitate consumers' ability to bond with the robot. On the other hand, in instances in which there is a significant mismatch between expectations and actual robot behaviour, it can lead to a negative evaluation of the interaction (Broadbent, 2017). In general, products that are more easily anthropomorphized yield long-term business success because they promote and foster brand user relationship, attachment and consequently loyalty (Chandler & Schwarz, 2010). According to Chandler and Schwarz (2010) this has an effect even on disposition because people are less willing to replace their car or computer if they thought of it in anthropomorphic terms.

The T*hree-Factor Theory of Anthropomorphism* developed by Epley, Waytz and Cacioppo (2007) identifies three psychological determinants of anthropomorphism: *elicited agent knowledge*, *effectance motivation* and *sociality motivation*.

Elicited agent knowledge (also called *need for cognition*) refers to the applicability of anthropocentric knowledge i.e. the applicability of knowledge about humans to make inferences about non-human agents (Epley, Waytz & Cacioppo, 2007). Indeed, individuals trying to understand non-human domains are likely to use knowledge about humans (if applicable) as a basis for induction. For instance, humans witnessing animal behaviour are likely to interpret it through a behavioural human schema. In other words, when people attempt to comprehend phenomena and behaviours in domains they have little experience in (for example animal or robot behaviour) they are likely to associate what they are witnessing to more familiar phenomena and behaviours that are common in human beings so that they can better understand the environment around them. This is because this kind of knowledge is more readily available, more salient and it tends to be more detailed than knowledge about non-human agents. People have a tendency to use information they understand, and they are familiar with, to comprehend things they are not knowledgeable about (Epley, Waytz & Cacioppo, 2007).

Effectance motivation (also called *need for control*) refers to the desire for interacting effectively with the surrounding environment (Epley, Waytz & Cacioppo, 2007). Applied to the concept of anthropomorphism, it involves the need to understand the complex set of stimuli produced by the non-human agent and gaining control over the situation. Attributing human-like characteristics to the non-human agent is thus a way to simplify this process and reduce uncertainty. It enhances the individual's ability to comprehend the non-human agent's behaviour and it strengthens the individual's confidence in future predictions of the agent's actions. In this sense anthropomorphism is a way to reduce the anxiety and uncertainty provoked by the unfamiliar form of interaction (Epley, Waytz & Cacioppo, 2007).

Sociality motivation (also called *chronic loneliness*) refers to the need to establish connections with human agents (Epley, Waytz & Cacioppo, 2007). This leads people in absence of connections with other humans to satisfy their need for affiliation with anthropomorphized non-human agents (Epley, Waytz & Cacioppo, 2007).

This theory implies that people are more likely to anthropomorphize in instances in which anthropocentric knowledge is salient and applicable (for example when visual or behavioural cues of the robot suggest a similarity with human beings), when they have a need for making sense of the reality they are interacting with (for example when social anxiety motivates individuals to reduce uncertainties), and when they lack connection with other humans (Epley, Waytz & Cacioppo, 2007). In general (although with some exceptions) consumers tend to prefer anthropomorphized products to non-anthropomorphized ones. This happens because anthropomorphising products gives them a feeling that they are interacting with some familiar elements (people like what they are familiar with), because it enhances the perception of control over the situation, and because it gives them a sense of connection (Epley, Waytz & Cacioppo, 2007).

According to Broadbent (2017), one of the effects of anthropomorphism is that people mindlessly apply human social rules to robots. It has been demonstrated that some people have a tendency to treat some inanimate objects (cars, computers etc..) like human beings. Indeed, the author argues that people have a tendency to use stereotypical social categories like ethnicity, gender and in-group-out-group considerations when judging or using objects like computers. For instance, Nass, Moon and Green (1997) showed that computers with a female voice are perceived as more emotional and more knowledgeable about relationships and love with respect to computers with a male voices who are perceived as more rational despite the computers in the experiment provided the same information. Gender associations affect the evaluation of autonomous vehicles as well as robots (Broadbent, 2017). Indeed, Waytz, Heafner, and Epley (2014) demonstrated that people trust an autonomous vehicle with a feminine voice more than an autonomous vehicle with a masculine voice. In addition to that, people have a tendency to believe that an autonomous vehicle performs more mindfully a task as it acquires more anthropomorphic features like a human voice and a human name. Moreover, increased anthropomorphism leads to mitigation of blame for the autonomous vehicle involvement in undesirable outcomes (Waytz, Heafner, & Epley, 2014). For what concerns robots, participants in an experiment responded more positively to a donation request from a female-looking robot and rated female-looking robots as more trustworthy, engaging, and credible (Siegel, Breazeal & Norton, 2009). Furthermore, Nass and Moon (2000) demonstrated that in the context of computer agents, when participants were exposed to virtual agents of their same ethnicity, they rated them as more trustworthy, attractive, intelligent, and persuasive compared to out-group virtual agents. Another interesting effect of this application of human social rules was found by Fogg and Nass (1997) and it relate to reciprocity of behaviours and of self-disclosure. The authors demonstrated through an experiment that people were willing to spend more time and help more accurately a computer to perform a certain task if the computer previously supported them in performing another task and similar responses were elicited with robots. For what concerns reciprocal self-disclosure, Moon (2000) showed that people are more willing to disclose personal information if the computer provides them with information about itself. In addition to this, Hoffman et al. (2015) proved that the social presence of a robot elicits the same reactions on honesty as the social presence of a human being. In fact, when people were asked to perform a task in a room with a robot, they felt as if they were being watched and this increased their honesty. These are clear examples of non-human-human interactions that elicit responses and behaviours similar to the ones elicited by as human-human interactions. Anthropomorphism facilitates this process (Broadbent, 2017).

However, the fact that people associate inanimate objects, and in particular robots, to human schema and that they interact with them applying human social schema does not mean that they perceive humans and robots to have the same kind of mind (Broadbent et al., 2013; Broadbent, 2017). Indeed, Gray, Gray and Wegner (2007) demonstrated that robot’s minds are perceived as different from human minds both in terms of agency (i.e. self-control, morality, memory, emotion recognition, planning, communication, and thought) and capacity for experience (e.g., hunger, fear, pain, pleasure, rage, desire, personality, consciousness, pride, embarrassment, and joy). Participants in their study rated robots as having little capacity for experience but moderate agency while they rated adult humans to score high on both dimensions. Interestingly, perceptions of robot minds change for different robots (Broadbent et al., 2013; Broadbent, 2017). For example, in an experiment conducted by Broadbent et al. (2013), when the robot had a face on a screen, it was not only more easily anthropomorphized, but it was also perceived as having more agency and capacity for experience with respect to a robot with no face at all. This means robots with anthropomorphized and mechanized designs differ in their ability to elicit perceptions of these dimensions (Broadbent et al., 2013; Broadbent, 2017). This can affect the extent to which people are willing to trust robots with different designs (Broadbent et al., 2013; Broadbent, 2017).

Van Pinxteren et al. (2019) analysed how different cues lead to anthropomorphism in different individuals. Indeed, although it had been shown that anthropomorphism drives trust, it remained still unclear which features were more relevant in this process. More specifically, the authors investigated what kind of cues allow people to anthropomorphize more easily a service robot. The two classes of cues that were analysed were observable humanlike features such as having a humanlike appearance (humanlike face, eyes body etc…), and human like social functioning features such as the ability to mimic humanlike nonverbal communication cues. The reason why this analysis is extremely relevant is that service robots that are designed to mimic human social functioning cues do not necessarily exhibit observable human-like features. Indeed, for the reasons mentioned in the uncanny valley section, a sense of uncanniness can be triggered by robots exhibiting facial expressions extremely similar to the ones of human beings but not perfectly matching those expressions. For this reason, one of the design solutions applied to provide social functioning cues without eliciting a sense of discomfort has been dynamic eye colour to mimic body cues that humans provide during social interactions (van Pinxteren et al. 2019). Different eye colours signal different moods of the robot and whether it understood or not the person it is interacting with. Robots with such characteristic violate human-like observable features, in the specific case mentioned, a robot exhibiting humanlike observable cues would have a static eye colour to look more similar to a human being (van Pinxteren et al. 2019). The authors discovered that cues more effective in facilitating anthropomorphising of service robots change with different levels of discomfort caused by the robot (different levels of robot anxiety, attitudes towards robot etc…). In particular, participants that were experiencing high discomfort in the interaction with the robot were more likely to anthropomorphize it (and consequently they trust it more) if it exhibited social functioning cues as opposed to observable humanlike cues. In contrast to that, people that were confident in HRIs anthropomorphize robots more easily (and consequently they trust it more) when they exhibit observable humanlike cues as opposed to social functioning. In other words, people that are at unease with robot interactions prefer robots that behave like humans while people that are at ease with robot interactions prefer robots what look like humans. An explanation provided by the authors is that people who experience discomfort with HRIs perceive the interaction to be more unpredictable with respect to participants who do not experience discomfort. Thus, they appreciate robots that behave more like humans (through social functioning cues) because that gives participants a way to predict robot behaviour and consequently allowed them to regain control over the uncomfortable situation. The authors suggest that a similar mechanism could occur in contexts in which discomfort is caused by other sources other than the robots (van Pinxteren et al. 2019). However, this was not properly demonstrated.

2.4.3- Cuteness

Cute design has been widely used especially in social robots to convey warmth and decrease the perception of threat and related concerns (Nenkov & Scott, 2014). Nenkov and Scott (2014) defined cuteness as a feature of object or agents that make them attractive in an adorable or endearing way. This particular design has become a predominant design especially for companion robots and social robots (Caudwell, Lacey, & Sandoval, 2019). They sometimes include humanlike features because there is evidence that this can enhance perceptions of cuteness (Nenkov & Scott, 2014). According to Nenkov and Scott (2014), cuteness is a broad concept that can be affected by several characteristics such as shape, size, marketing positioning and overall design of the product. The authors divided cuteness into two constructs: *baby schema cuteness* (also termed *kindchenschema cuteness*) and *whimsical cuteness* that elicit different reactions in people. *Baby schema cuteness* is elicited by products that exhibit some characteristics typical of children and new-borns. Some examples provided by the authors of designs of baby schema cute products include big eyes, high pitched voices, and rounded cheeks. Because they foster associations with vulnerable creatures, naïveté, kindness, honesty, and warmth these products elicit reactions in adults like increased attention and caretaking behaviour. According to the authors, these reactions are not limited to affective states, but they also influence cognitive processes and behaviours. An explanation provided by Sprengelmeyer et al. (2009) for these reactions is related to an evolutionary hormonal response to spur adults to take care of their offspring. On the other hand, whimsical cuteness does not trigger this process caused by the association with vulnerability (Nenkov & Scott, 2014). Indeed, whimsically cute design is associated with playfulness and fun. Moreover, whimsical cuteness was shown to trigger indulgent behaviour while this was not the case for baby schema cuteness (Nenkov & Scott, 2014).

Caudwell, Lacey and Sandoval (2019) argued that behaviours of caretaking triggered by baby schema cute design can establish the ground for long-term strong bonds. Indeed, they proved that cuteness increases the likelihood of customers getting addicted to products. However, they argue that in the context of service robots this effect is more complex. Their research shows that if the robot does not appear to grow and evolve over time the benefits of cuteness are short lived and only provoke short term engagement. Moreover, if cuteness is perceived as unnecessary, for example in contexts in which interaction is not crucial (as in the case of utilitarian robot) the effect of a cute design become negligible. It is then extremely important to consider the adaptability of the robot as well as the context in which it will be used to assess whether a cute design should be implemented (Caudwell, Lacey & Sandoval, 2019).

Another reason why cute design can be beneficial in Human-Robot interactions is that they enhance our tolerance for algorithmic mistake because we associate baby-schema cute design to kids that are still learning and in general people tend to have higher tolerance for humanized devices when they make mistakes(Waytz,, Heafner & Epley, 2014). Indeed, as a result of anthropomorphism, we tend to apply stereotypical social categories to machines and computers (Broadbent, 2017; Nass, Moon & Green, 1997; Waytz, Heafner & Epley, 2014). Cuteness, and baby schema cuteness, have the effect of priming people towards infant associations lead to caretaking behaviour (Nenkov & Scott, 2014). This increases our tolerance for algorithmic mistake because it elicits people’s perception that the robot is evolving like children would do (Nenkov & Scott, 2014). Indeed, according to algorithm aversion theory, the main reasons for discounting and distrusting algorithmic advice are: inability of agents powered by artificial intelligence to learn, adapt to different situations and to incorporate qualitative data (Dietvorst, Simmons & Massey, 2015). Because baby schema cuteness triggers associations with children which are characterized by a constant process of learning and adaptation, this can decrease aversion to algorithmic (and robot) advice (Nenkov & Scott, 2014). A further advantage of associations to vulnerable creatures is the consequent decrease in perceived threat during the interaction (Nenkov & Scott, 2014). This is extremely important in order to foster trust in HRIs (Waytz, Heafner & Epley, 2014).

2.5 – TRUST IN ROBOT AND ROBOT'S ADVICE

When decision-makers receive advice, they are potentially exposed to the instance in which their opinion conflicts with the advisors' opinion. In such instances people are faced with the options of fully adopting the advisor's suggestion, partially integrating it (for instance averaging the opinions) or fully ignoring it. Yaniv and Kleinberger (2000) proved that although use of advice tends to increase accuracy of judgements, people have a tendency to overweight their opinion with respect to other people's one and this usually results in discarding the advisor's suggestion. This phenomenon is usually referred to as *overconfidence* and it is the consequence of what Yaniv and Kleinberger (2000) have defined *egocentric discounting*. According to them, this phenomenon is caused by the fact that decision-makers usually have privileged access to information about the reasons that led the to the beliefs they hold, but only limited information about the reasons that led the advisor to form a certain opinion. This asymmetry in the availability of supporting information for the opinion of the decision-maker and of the advisor leads to discounting of the advisor' suggestion (Yaniv & Kleinberger, 2000).

Another explanation for advice discounting and overconfidence comes from *anchoring and insufficient adjustment* (Tversky and Kahneman, 1974) and it is caused by people's tendency to use their initial judgement as an anchor and information received in the form of the advice are used to make adjustments to their initial judgement. However, such adjustments are insufficient because the initial judgement biases to much decision-makers who are "anchored" to their initial opinion. A third explanation for this effect was proposed by Krueger (2003) and it is usually referred to as *egocentric bias explanation*. According to Krueger (2003) a perception of individuals' superiority with respect to other people drives them to discount their opinion and, as a consequence, advisors' suggestions.

It should be noted that this effect does not hold constant regardless of the task. Gino and Moore (2006) demonstrated that weight on advice –which is the extent to which advice is integrated in the decision making-changes with perceived difficulty of the task. More specifically, when the task is perceived as difficult, people exhibit a tendency to overestimate advice while they tend to underestimate advice when they perceive a task to be relatively easy. They confirmed this pattern occurs both when people are given automatically the advice and when they must actively seek for it. This happens because while people tend to believe that they are better than others when it comes to simple tasks, they tend to believe the opposite when it comes to difficult tasks (Gino & Moore, 2006). This would suggest that novices, who have not developed a refined expertise and skills as most experts have, are more likely to perceive tasks as difficult and consequently to highly rely on advice while the opposite is true for experts.

When people evaluate whether to trust or not an advisor, they spontaneously form an opinion of the advisor and this reputation affects the extent to which his advice will be taken into consideration (Yaniv & Kleinberger, 2000). Usually, positive experiences and impressions lead to higher trust while negative ones lead to lower trust. However, Yaniv and Kleinberger (2000) showed that the way positive and negative experiences and associations shape the reputation of the advisor is not the same. In fact, people perceive negative information as more diagnostic and salient with respect to positive information. As a consequence, negative information is more influential in shaping the advisor's reputation. The authors refer to this effect is as *negativity bias.* An explanation provided in the study for this asymmetry in the influential power of positive and negative information lies in the fact that negative information signals that the other individual deviates from the social norms and expectations of the decision-maker and this makes the experience more salient. This has implications on reputation formation and adjustment. Indeed, while gaining trust is a slow process that can require various positive experiences, fewer negative information is needed to dramatically and quickly alter the reputation gained over time (Yaniv & Kleinberger, 2000). Because robot advice is basically algorithm advice, it faces a series of challenges such as algorithm aversion (Dietvorst, Simmons, & Massey, 2015). As a consequence, for robot advisors to be effective in shaping consumer behaviour it is important that they are designed in such a way to promote robot trust and to foster advice compliance.

Interestingly, participants in the study conducted by Yeomans et al. (2019) liked algorithmic recommendations because they were more accurate, but they liked and trusted better human recommenders. According to the authors, the reason for this algorithm aversion is related to the fact that people prefer recommendations based on a reasoning process they can easily understand. Because the algorithmic evaluation process is perceived as more difficult to understand than the human one, people tend to exhibit preference for human advice. In other words, Yeomans et al. (2019) proved that people tend to trust less algorithmic advice with respect to human advice because they perceive human decision-making process as more easily understandable than algorithmic one: people trust what they feel they can understand. However, these perceptions of subjective understanding can be altered enhancing transparency of how the algorithm works. In addition to that, the experiment showed that participants' reaction towards recommendations differed depending on whether they believed that the source was human or algorithmic so that they perceived the very same advice as less transparent when participants thought that it came from an algorithm and more easily understandable when they thought it came from a person (the advice was in fact generated by an algorithm). The authors claim that such aversion is to some extent rational because it is the result of technophobia. Since people are more familiar with human recommendation processes than algorithmic ones, initial reluctance to follow algorithmic advice and preference for human advice is quite natural (Yeomans et al. 2019).

It could be argued that because novices are not able to understand the human recommendation due to lack of product or service knowledge, the effect of lower subjective transparency of algorithmic recommendations with respect to human recommendations might be smaller for novices as opposed to experts. And as a consequence, novices could be expected to have a more positive attitude towards the AI-powered technologies. In addition to that, Yeomans et al. (2019) suggest that subjective understanding could be altered increasing the transparency of algorithms. In fact, in one of their experiments, participants who received a more detailed explanation of how the algorithm operated had a higher opinion of the performance of the recommender and trusted the algorithmic advice more.

In addition to that, a study conducted by Buell and Norton (2011) demonstrates that including features that people might associate to human behaviour improves people's perception of the algorithmic performance. For instance, a website signalling that is "making an effort" or that is "processing data" instead of immediately giving a response, triggers associations to humans who cannot provide immediate responses for difficult tasks and must actively process information before answering. This simple technique positively affected people's opinion of the website suggesting that humanlike features such as human like appearance and presence could increase compliance to algorithmic advice. In the field of robotics de Graaf and Allouch, (2013), Broadbent (2017), Chandler and Schwarz (2010), Aggarwal and McGill (2007), Epley, Waytz and Cacioppo (2007), Waytz,, Heafner, and Epley (2014) and Siegel, Breazeal and Norton (2009) have suggested that human like features and physical presence of the robot increase trust in the machine but to the date no study has analysed yet whether these or other features can increase compliance to robot advice which ultimately is algorithmic advice. This seem to suggest that increasing human-like features both in terms of appearance and behaviour could increase compliance with advice.

Extensive literature proved that trust is a strong determinant of purchase and use of services and products, and some studies have focused on the role of trust on TBSS, robots and virtual agents. In the particular context of service robots, trust Wirtz et al. (2018) identified as one of the main antecedents of robot acceptance in the service Robot Acceptance Model (sRAM). Trust was defined as a multidimensional concept that reflects integrity, benevolence, and competence of another entity (van Pinxteren, et al. 2019). Trust, and in particular emotional trust, involves comfort experienced about depending on the trustee (Wirtz et al., 2018). According to Wirtz et al. (2018), two key dimensions that were demonstrated to play a crucial role in perceptions of trust are competence (ability to perform effectively a task) and warmth (ability to display empathy and interest in customer's interest). This is because for people to follow an agent's advice it is important for them to believe that the agent's advice is valid but also in their best interest. According to Wirtz et al (2018) eliciting perceptions of robots' warmth is more challenging than eliciting perception of robot's competence. This is because programming robots to detect and appropriately respond to customer emotional states is more complex than programming them to perform cognition-oriented tasks. In fact, according to Waytz and Norton (2014) robots in general are more likely to be perceived as possessing cognitive skills (and thus competence) than as possessing emotional skills (and thus warmth).

Another challenge when it comes to inspiring trust stems from algorithm aversion proposed by Dietvorst, Simmons and Massey (2015). According to them, this disposition leads people to tolerate and forgive better human mistake with respect to algorithmic mistake. In fact, they proved that after people see algorithms err, they are less likely to follow algorithmic advice even if they see them outperforming human advice consistently. However, it should be noted that Logg, Minson and Moore (2019) showed that when algorithmic mistake is not directly imputable to the virtual agent, people are less likely to discard advice when it comes from an algorithm than when it comes from another person. This effect is even stronger for novices than for experts in the advice domain matter, suggesting that service robots may be more easily trusted by novices than by experts (Logg, Minson & Moore, 2019).

Trust was also demonstrated to be a critical factor in enjoyment in HRI (Broadbent, 2017; van Pinxteren et al. 2019) and in actual use of service robots and virtual agents (Wirtz et al., 2018). For this reason, robots and virtual agents are usually designed with specific features aimed at inspiring trust to make people more comfortable in interacting with them (Broadbent et al., 2013). There is ambiguity concerning the features that are more likely to inspire trust. van Pinxteren et al. (2019) suggested that this happen because the effectiveness of these characteristics is context specific. In other worlds, the very same feature can elicit different reactions in consumers based on factors such as people's comfort with HRIs (van Pinxteren et al. 2019), people tendency to anthropomorphize inanimate objects (Aggarwal & McGill, 2007; Epley, Waytz, & Cacioppo, 2007; Waytz, Heafner, & Epley, 2014), individuals psychological traits (Ivaldi et al, 2016) and more.

One of the drivers of service robot trust has been identified as anthropomorphism, and for this reason a wide variety of service robots has been conceived in such a way to elicit associations to human beings (van Pinxteren et al. 2019). Indeed, some authors found evidence that when humans ascribe humanlike characteristics such as a human like mind and empathy to non-human agents they are more likely to trust those agents (Aggarwal & McGill, 2007; Epley, Waytz, & Cacioppo, 2007; Waytz, Heafner, & Epley, 2014; van Pinxteren et al. 2019). This happens because associations with humanlike minds and feelings cause an increased perception of competence and warmth of those agents (Fiske, Cuddy & Glick, 2007). However, as it was discussed in the anthropomorphism section, the way people anthropomorphize is not identical for all individuals (Epley, Waytz & Cacioppo, 2007). Indeed, van Pinxteren et al. (2019) demonstrated that anthropomorphism can be elicited by different kinds of cues, namely humanlike observable cues, and humanlike social functioning cues. The extent to which such cues are effective at facilitating individuals' likelihood of anthropomorphising depends on the level of comfort experienced during HRIs. As a consequence, because anthropomorphism drives trust, this implies that different kind of cues are more or less effective in generating robot trust depending on individuals' level of comfort in HRIs. In other words, people experiencing high levels of HRIs discomfort are more likely to anthropomorphise and trust robots that communicate like human beings while people experiencing low levels of HRIs discomfort are more likely to anthropomorphise and trust robots that look like human beings (van Pinxteren et al. 2019). However, it is unclear if similar effects on trust occur in situations in which levels of discomfort varies for reasons different from comfort with service robots. For example, it is possible that discomfort stemming from embarrassment may elicit similar reactions in people.

Moreover, there is disagreement about the effects of anthropomorphism on trust. Some authors like Wirtz et al. (2018), Mathur and Reichling (2016) showed that although humanlike attributes in robots inspire trust they do so only up to a certain level of humanness because of the *uncanny valley law* (Mori, 1970; Mori, MacDorman, & Kageki, 2012). In addition to that, Mende et al. (2019) proved that HRI discomfort and service robot anxiety is lower when participants interact with mechanized service robots (as opposed to anthropomorphised service robots). Indeed, according to Mende et al. (2019), designing service robots in a way that deviates from human appearance leads to a lower sense of uncanniness and category confusion. This effect is extremely important because people experiencing robot anxiety have a tendency to trust service robots less with respect to individuals not experiencing robot anxiety (Broadbent, 2017). However, discrepancies in these results could be attributed to the fact that Mende et al. (2019) focused specifically on instances in which individuals were experiencing discomfort in the HRI due to service robot anxiety. This could mean that while people experiencing severe service robot anxiety allocate higher trust in mechanized robots, people not experiencing such emotional state may prefer anthropomorphized service robots. This implies that selecting the appropriate design on a human-machine continuum is extremely challenging and a careful analysis of customers potential reactions and preference should be to maximise trust in service robots.

The use of cuteness in robot design also has important implications on trust in robot and in robot advice (Nenkov & Scott, 2014; Waytz, Heafner & Epley, 2014). Indeed, it was demonstrated that cuteness can lead to increased tolerance for algorithmic mistakes through the established associations with infants. Moreover, these associations were proved to increase perceptions of warmth, decrease fear of the robot. These effects are extremely beneficial for customers exhibiting moderate but significant levels of robot anxiety. However, associations to naïve and inexpert creatures has also the effect of decreasing perceptions of competence which can be extremely detrimental because savvy customers may perceive robot advice as overly unsophisticated and discard it. This suggests that the use of cuteness in service robots can have ambiguous effects on robot trust and, more importantly, that target customers characteristics should be taken into account before implementing this kind of design (Nenkov & Scott, 2014; Waytz,, Heafner & Epley, 2014).

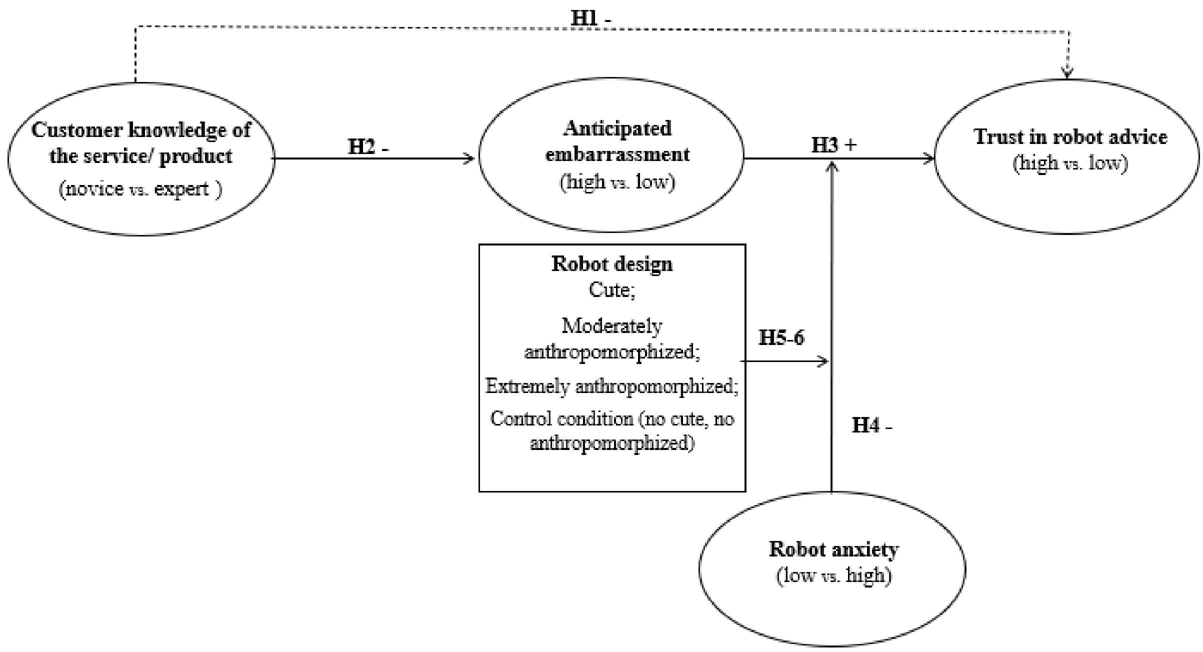
CHAPTER 3 - EMPIRICAL STUDY

3.1 - MODEL

The research question of the current study concerns the effect of customer knowledge on trust in robots and the role of embarrassment, robot anxiety, and robot design in such process. Indeed, Miller (1996) demonstrated that lack of customer knowledge can result in anticipated and perceived embarrassment during the service encounter. This emotional state can result in undesirable behaviour of interaction avoidance, which could be compensated by an increased willingness to seek advice from non-human agents like robots and virtual assistants.

The desire to reduce anticipated embarrassment stemming from social interactions could have an effect on the willingness to follow the service robot's advice. This could result in increased trust in the robot's competences and in the robot as a whole. It should be noted that, because trust plays a crucial role in the adoption of service robots, this finding would have important implications on service robot adoption. In fact, this could demonstrate that customer knowledge plays an important role in shaping attitudes towards service robot and should be used as a behavioural segmentation variable in this context. However, the effect of customer knowledge and consequent embarrassment on service robots trust remains unclear, and with the present work I purport to contribute to a better understanding of the relation between knowledge and embarrassment in relation to service robots.

Moreover, design of service robots could moderate this effect however and there is no existing literature on its effect in this specific context. In fact, robot anxiety has been demonstrated to have a strong impact on perceptions of service robots and, for this reason, it could moderate the effect of embarrassment on trust. To overcome this problem, robot design was demonstrated to moderate robot anxiety and can then be expected to influence the effect of robot anxiety on the effect of embarrassment and trust in robots. Graphically the model of this study can pe portrayed as follows:



Novices and experts undergo significantly differences processes when forming an opinion about a product or a service. Among the most important differences prior literature identified disparities in: ability to perform task-related activities (Alba & Hutcherson, 1987), cognitive tools available for decision making (Alba & Hutcherson, 1987), cognitive biases (Kahneman, 2011; Tversky & Kahneman, 1974), the decision making process in terms of efficiency and efficacy (Kahneman, 2011; Park & Lessing, 1981), inputs used in the decision making process (Park & Lessing, 1981), relative weight assigned to each input (Mittal, Kumar & Tsiros, 1999; Bettman & Park, 1980; Brucks, 1985; Rao & Monroe, 1988; Devlin, 2011; Dagger & Sweeney, 2007), preference for interaction methods (Knijnenburg, Reijmer, & Willemsen, 2011), the extent to which they rely on advice and confidence in the decision outcome (Alba & Hutcherson, 1987; Kahneman, 2011; Park & Lessing, 1981; Dietvorst, Simmons, & Massey, 2015; Logg, Minson & Moore, 2019) .

Indeed, experts have been demonstrated to achieve superior efficiency and efficacy indecision making using both more complex processes and skill-driven mental shortcuts (Kahneman, 2011; Park & Lessing, 1981. However, because they highly rely on their own intuitions, they are subject to biases such as overconfidence which makes them less likely to rely on others' advice (Kahneman, 2011; Healy & Moore, 2007; Gino & Moore, 2006). On the other hand, novices are more likely to be tempted to use more linear decision making processes and rely on signalling attributes (non-functional and search attributes) because they are not able to fully integrate more complex information and because they are subject to the availability bias (Alba & Hutcherson, 1987; Park & Lessing, 1981; Kahneman, 2011; Tversky & Kahneman, 1974). They are also more likely to rely on others' advice because it helps them overcome their lack of knowledge (Alba & Hutcherson, 1987; Gino & Moore, 2006). Differences on advice reliance are amplified when the source of advice is non-human (Yeomans et al. 2019; Dietvorst, Simmons, & Massey, 2015; Logg, Minson & Moore, 2019). Prior literature on algorithm aversion and appreciation, although divergent in several findings, established some common ground in the idea that experts discard more algorithmic advice than novices do (Dietvorst, Simmons, & Massey, 2015; Logg, Minson & Moore, 2019). It can then be expected that a similar pattern of behaviour would occur when the source of the advice is a robot. In addition to that, the fact that novices are more likely to perceive a task within the service encounter more difficult with respect to experts, makes them more likely to rely on advice. This is because Gino and Moore (2006) demonstrated that perceived task difficulty increases reliance on advice regardless of its source. Consequently, this work theorizes that experts and novices within the context of a specific product/service differ with respect to the extent they trust robot advice. More specifically

H1: Novices (experts) of a specific product or service domain are more (less) likely to trust robot advice

Lack of customer knowledge of the service or product makes novices more likely to be subject to negative emotional states such as embarrassment. Indeed, prior literature demonstrated that lack of customer knowledge can lead to perceptions of inability to perform correctly the customer role in the service script and trigger fear of negative evaluations by others and lead to discomfort (Alba & Hutcherson, 1987; Grace, 2007; Higuchi & Fukada, 2002). In addition to that Miller (1996) empirically proved that lack of previous experience with a certain event positively correlates with perceived and anticipated embarrassment. According to Grace (2007), lack of knowledge is a triggering factor of both the antecedents of embarrassment identified by *Dramaturgic* (Higuchi & Fukada, 2002) and *Social Evaluation Theories* (Miller, 1996;). According to *Dramaturgic Theory*, embarrassment in the service encounter is caused by a perception of inability to behave appropriately in the specific service encounter context (Higuchi & Fukada, 2002). In other words, concerns about disrupting social performance and inability to perform the customer role in the service script leads to service encounter embarrassment. (Higuchi & Fukada, 2002). According to *Social Evaluation Theory*, the presence of a service employee can trigger fear of being negatively evaluated which leads to concerns for the portrayed self and, as a consequence, to anticipation of embarrassment (Miller, 1996). Because lower levels of customer knowledge are more likely to produce inabilities to follow correctly the steps in the service script (Dahl, Manchanda & Argo, 2001) and because such inabilities are likely to provoke perception of negative evaluations, this work theorizes that low levels of customer knowledge lead to higher embarrassment perceived in the service encounter. Formally:

H2 Novices (experts) of a specific product or service domain are more (less) likely to experience embarrassment due to lack of customer knowledge

Moreover, the effect of customer knowledge on robot trust is mediated by a perceived sense of embarrassment caused by lack of customer knowledge which leads to increased trust in robot and robot advice. Indeed, when customers with little knowledge expect a service encounter with a human being to be potentially embarrassing

– both because of potential inability to act properly in the service encounter or because of fears of negative evaluations – they are likely to engage in coping behaviours to avoid anticipated embarrassment (Miller, 1996; Higuchi & Fukada, 2002; Grace, 2007). In the context of purchase of embarrassing goods technology-based self-service has been proved to be highly beneficial because the reliance on such devices allowed customers to avoid social interactions (Londono, Davies & Elms, 2017). It should be noted that it has been demonstrated that a sort of affective loss aversion occurs such that motivation to preserve self-image is stronger than enhancement of self-image (Baumeister et al. 2001). In other words, the concern for self-image strongly affects behaviour and can it lead to a series of coping behaviours aimed at preventing anticipated embarrassment (Baumeister et al. 2001; Grace, 2007). An element proved to increase perceptions of negative evaluations is the so-called *spotlight effect,* which is the phenomenon according to which individuals overestimate how harshly they are being evaluated by others and the extent to which others notice embarrassing situations in which individuals are involved (Gilovich & Savitsky, 1999). Increased reliance and trust in robot advice could be an effective strategy for customers anticipating embarrassment to avoid human social interaction and, as a consequence the negative emotional state that stems from it. It can be expected that when advice is needed but embarrassment is anticipated customers may be more willing to rely on robot advice complying to it such that:

H3 higher levels of embarrassment lead to higher trust in robot advice

However, it should be noted that previous effects of embarrassment on robot trust are not unconditional. Indeed, a vast literature in robotics has identified a common human negative reaction to robots, namely robot anxiety (Mori, 1970; Mori, MacDorman, & Kageki, 2012; Mathur & Reichling, 2016; de Graaf & Allouch, 2013; Nomura et al. 2006; Mende et al. 2019). There are several elements that trigger this sense of fear, uncanniness, and revulsion towards robots (Mori, 1970; Mori, MacDorman, & Kageki, 2012; Mathur & Reichling). Some fears relate to threats to human identity or job loss (Mende et al. 2019; Waytz & Norton, 2014). The former involves concerns about the meaning of life and the threat that robots pose to the humankind (Mende et al. 2019), the latter concerns the fear of people being substituted by robots and losing their job (Waytz & Norton, 2014). Others are the result of an evolutionary process such as a disease avoidance mechanism triggered by the association of robots to corpses (Broadbent, 2017; MacDorman, 2005). Indeed, according to Broadbent (2017) robots often trigger associations with corpses that elicit a sense of revulsion. MacDorman (2005) proposed that these associations with corpses increase salience of human mortality and for these reasons people have a tendency to develop negative attitudes towards robots which often take the form of fear. Another important cause of robot anxiety is category confusion and lack of familiarity which makes people wary of robots (Broadbent, 2017). This happens because most people have little in depth-knowledge of robots as well as previous direct experience with them (Broadbent, 2017). People tend to like what they are familiar with and mistrust agents that they do not understand and thus, whose behaviour is perceived as unpredictable (Broadbent, 2017). Because this negative attitude towards robots frequently results in avoidance of human-robot interaction, this can decrease trust in robot advice. Indeed, robot anxiety can be expected to algorithm aversion which is a phenomenon according to which people discard algorithmic advice (Dietvorst, Simmons, & Massey, 2015). As a consequence, it can then be expected that robot anxiety moderates the effect of embarrassment on robot trust because it prevents people from comfortably interacting with service robots diminishing or nullifying the effect of embarrassment on trust in service robot.

H4 robot anxiety decreases the effect of embarrassment on trust in robot

According to prior literature in the field of robotics, an important factor diminishing robot anxiety is robot design (Broadbent, 2017). Design is extremely effective in diminishing robot anxiety because it manages to deactivate negative association to robots (such as the ones related to corpses) and it activates positive associations to characteristics such as competence, warmth and harmlessness (Nenkov & Scott, 2014; Waytz, Heafner & Epley, 2014). Moreover, design can increase perceived familiarity and decrease category confusion through features that remind customers of familiar concepts that they easily understand (Broadbent, 2017). For instance, a robot shaped like a cute animal (see Paro) is easily associated with a harmless puppy and its behaviour is perceived to be more predictable (Nenkov & Scott, 2014). As a consequence, this work theorizes that the moderating effect of robot anxiety on the effect of embarrassment on trust in robot is moderated by the design of the robot.

The use of anthropomorphism in robot design is one of the most discussed issues in robot design (Broadbent, 2017). Indeed, some authors suggested that mechanized design (as opposed to anthropomorphized) is more appropriate because it deactivates the *uncanny valley effect* (Mende et al. 2019). However, it should be noted that the study sustaining this finding have been conducted in contexts in which participants were exhibiting high levels of robot anxiety. It would then make sense not to focus on those customers because naturally inclined to avoid robots (Mende et al. 2019).

On the other hand, various authors demonstrated several benefits of anthropomorphized designs when participants were not exhibiting excessive robot anxiety (de Graaf & Allouch, 2013; Broadbent, 2017; Chandler & Schwarz, 2010; Aggarwal & McGill, 2007; Epley, Waytz & Cacioppo, 2007; Waytz,, Heafner, & Epley, 2014; Siegel, Breazeal & Norton, 2009; van Pinxteren et al. 2019). Among these we find positive associations and positive attitudes towards robots as well as increased perceptions of warmth, competence and familiarity (Broadbent, 2017). It should be noted that although these positions seem conflicting, they simply occur when people experience different levels of robot anxiety. Thus, when robot anxiety is extremely high it is possible to expect a more positive reaction to a robot with a mechanized design (Mende et al. 2019), however when the robot anxiety is not paralyzing, it is reasonable to expect people to react more positively to a robot with an anthropomorphized design (de Graaf & Allouch, 2013; Broadbent, 2017; Chandler & Schwarz, 2010; Aggarwal & McGill, 2007; Epley, Waytz & Cacioppo, 2007; Waytz,, Heafner, & Epley, 2014; Siegel, Breazeal & Norton, 2009; van Pinxteren et al. 2019). A further consideration should be made about the degree of similarity with human beings. Indeed, studies about the *Uncanny Valley Law* showed a positive relation between human likeliness and perceptions of trustworthiness of robots (Mori, 1970; Mori, MacDorman, & Kageki, 2012; Mathur & Reichling, 2016). However, this condition held up until a point where realism of robot was excessive, and robots looked extremely similar to but not perfectly like human beings (Mori, 1970; Mori, MacDorman, & Kageki, 2012; Mathur & Reichling, 2016). Indeed, trust in robots decreased significantly when this happened because a sense of uncanniness was triggered (Mori, 1970; Mori, MacDorman & Kageki, 2012; Mathur & Reichling, 2016). Consequently, this work theorizes that anthropomorphised design reduces robot anxiety. However, when robots look extremely similar to human beings, their trust-worthiness decreases. More succinctly:

H5a When the robot possesses an anthropomorphized (mechanized) design, people experience low (high) robot anxiety

H5b When the robot possesses an extremely (moderately) anthropomorphized design, people experience high (low) robot anxiety

Another common design, especially in the context of social robots is the cute one. Cute design is usually selected to reduce perception of threat and increase intention to interact with the robot (Caudwell, Lacey, & Sandoval, 2019). In particular, a very common choice in robot design, baby-schema cute design, which triggers associations to naïve and vulnerable creatures (Caudwell, Lacey, & Sandoval, 2019; Nenkov & Scott, 2014). This tends to trigger high perceptions of warmth, and lower perceptions of threat (Nenkov & Scott, 2014). However, on a negative note, these associations can lead to lower perceptions of competence and can trigger algorithm aversion and push people to discard robot advice (Nenkov & Scott, 2014; Dietvorst, Simmons & Massey, 2015). However, in general, the higher perceptions of warmth tend to increase trust and diminish fear of agents, thus this paper theorizes that:

H6 When the robot possesses a cute (non-cute) design people experience low (high) robot anxiety

3.2 – RESEARCH METHOD

This study falls in the category of studies that used the Judge-Advisor System(JAS), in which participants are required to make a decision after being exposed to advice before committing to the final decision (Gino & Moore, 2006). These studies take various forms but they all they all feature a judge, which is usually the participant required to make the decision, and an advisor which provides some input that can be used by the judge to adjust its final decision (Gino & Moore, 2006). The outcome of the decision can be either a choice or a judgement (Gino & Moore, 2006). Choices in the JAS refer to a selection among various alternatives which are characterized by a qualitative nature. On the other hand, judgement tasks require participants to provide quantitative estimates (Gino & Moore, 2006). Moreover, JAS studies differ in the extent to which the advice is provided as default option or whether participants must explicitly ask for the advice for receiving it (Gino & Moore, 2006). Furthermore, the advice can come from different sources such as other participants, individuals who did not take part in the experiment algorithms and more (Logg, Minson & Moore, 2019). These studies allow to understand both the extent to which participants rely on the advisor's suggestion but also how such process contributes to accuracy of decision-making (Gino & Moore, 2006). In the current study the outcome of the decision is a choice, the advice is provided as default option and the advisor takes the form of a service robot.

3.2.1 - Pre-test procedure

On the service robot side, the hypotheses formulated and discussed in the section above rely on two main dimensions, that is the perception of anthropomorphism and cuteness, thus the aim of the pre-test was to verify whether the robot designs selected were perceived as anthropomorphized and cute as prior literature specifies. To do so, I have tested five comparative videos of five existing robots. Based on prior literature on robot design five robots have been selected as representative of each category: namely neither anthropomorphized or cute (Cruzr), anthropomorphized but not cute (Asimo), Cute but not anthropomorphized (Kuri), extremely anthropomorphized but not cute (Sophia) and lastly cute and anthropomorphized (Pepper). Criteria used for the selection of robots was based on literature on baby-schema cuteness and anthropomorphism.

Cruzr[4] has been chosen as control condition thus as neither anthropomorphized nor cute. In fact, although Cruzr has two tiny arms no other feature of the robot suggests a similitude with human beings. The robot can talk with an artificial voice, but it cannot detect nor reproduce any human-like emotion. The robot does not meet the criteria for the identification of anthropomorphized designs proposed by Broadbent (2017) because its body, face movements and voice do not resemble the human ones. Moreover, the robot does not meet the criteria specified by Nenkov and Scott (2014) to identify cute robot designs. In fact, the robot does not have

[4]See appendix B, figure 1 - *Cruzr (control condition): not anthropomorphized, not cute* (UBTECH Robotics, 2020)

big eyes (it does not have eyes at all), it does not have rounded cheeks (it does not have cheeks at all), it does not have a high pitched voice and it does not resemble an infant or a child (Nenkov & Scott, 2014).

Asimo[5] has been chosen as anthropomorphized because it matched the features explicated by Broadbent (2017) that characterized anthropomorphized designs. Indeed, Asimo has a human-like body with arms and legs, however, its facial features are not defined as the robot resembles an astronaut wearing a helmet. Moreover, Asimo's movements are fluid and human-like compared to other robots in the market, the fact that the robot walks rather than using wheels like most robots was expected to increase anthropomorphism of this design. Asimo is able to talk but its voice is a little artificial. None of Asimo's features matched the description of cute products provided by Nenkov and Scott (2014) so she was expected to be perceived as not cute.

Kuri[6] has been chosen because it matches the description of Nenkov and Scott (2014), in fact, its design resembles an infant as it exhibits big eye and rounded cheeks. The robot does not speak but it produces high-pitched sounds to greet people or to signal that it understood the person it is interacting with. High pitched voice has been identified by Nenkov and Scott (2014) as an important characteristic increasing perception of cuteness in robots. In addition to that the robot is very tiny compared to other robots and this is noticeable comparing the robot to other elements present in the video. The fact that the robot is so tiny was expected to trigger associations to harmless infants (Nenkov & Scott, 2014). Because the robot does not have a human-like look, it does not move like a human being and it does not speak this design was not expected to be perceived as anthropomorphized.

Sophia[7] has been chosen as extremely anthropomorphized and this was also confirmed by the fact that Wirtz et al. (2018) explicitly mentioned it as such. Sophia is a feminine humanoid robot that has a very human-like feminine voice and human-like name and these characteristics were predicted to increase anthropomorphism in machines by Waytz, Heafner, and Epley (2014). Sophia has incredibly human-like facial features, and it is able to reproduce human emotions almost perfectly. She has two arms but no legs, so she moves around on wheels. However, her arm movements are very fluid even if she cannot walk. None of Sophia's features matched the description of cute products provided by Nenkov and Scott (2014) so she was expected to be perceived as not cute.

Pepper[8] has been chosen as cute and anthropomorphized because it has a human-like body although it does not have legs, so it moves around on wheels. Its movement are fluid although it cannot walk and it is even able to reproduce a limited range of human emotions such as happiness or sadness through its body language and this is expected to increase perceptions of anthropomorphism (Broadbent, 2017). Pepper's facial features and

[5] See appendix b, figure 2 – *Asimo (moderately anthropomorphized condition): anthropomorphized, not cute* (Honda, 2020)
[6] See appendix b, figure 3 - *Kuri (cute condition): not anthropomorphized, cute* (Mayfield Robotics, 2020)
[7] See appendix b, figure 4 - *Sophia (extremely anthropomorphized condition): anthropomorphized, not cute* (Hanson Robotics, 2020)
[8] See appendix b, figure 5 - *Pepper (anthropomorphized and cute condition): anthropomorphized, cute* (SoftBank Robotics, 2020)

voice remind people of a child because it has big eyes, and rounded cheeks and high-pitched voices and these characteristics were predicted to increase perceptions of cuteness by Nenkov and Scott (2014).

To test these designs five comparative videos have been produced. To make sure that differences in perceptions of anthropomorphism and cuteness did not stem from differences in the videos they have been edited to be similar and show the robots in a homogeneous manner. Each video lasted 10 seconds. Each video included three sections which were collected on corporate websites' YouTube accounts. The first one showed the robot greeting a person, when the robot could talk the robot said "Hi I am *name of the robot*, It's a pleasure to meet you" in the case of Kuri, which cannot talk, the robot produced a high pitched sound used to show the person it is interacting with that it recognized its speaker. The second section showed the robot moving on wheels (Cruzr, Kuri, Sophia and Pepper) or walking (Asimo). The third section showed a close up on details of the robot. Even background music has been homologated to prevent effects to be biased by the background music, so each video had the same background melody.

Participants in this pre-test were 130 and were randomized into five groups each seeing a different video. The experiment has been conducted on Qualtrics and each respondent was asked to answered to some questions after being asked to imagine to think of the robot that they had seen as a robot operating in a store advising customers about products. Participants could choose to respond to the survey either in Italian or English.

Anthropomorphism (ANTHR). To test for anthropomorphism of robots, a three-item scale validated by Carpinella et al. (2017) to measure perceptions of anthropomorphism in robots has been used (α =.77). Participants have been asked to rate their impression of the robot on a bipolar five points scale along the dimanesions of Machine-like/Human-like, Mechanical/Organic and Artificial/Life-like.

Cuteness (CUTE). To test for cuteness of robots, a three-items-scale validated by Hellén and Sääksjärvi (2013) to measure cuteness in robots has been used (α = .92). Participants have been asked to rate their impression of the robot on a seven-point Likert scale (from *1 – not at all* to *7 – very much*) along the dimensions of Cute, Sweet and Adorable.

Trust (TRUST). Moreover, to have preliminary understanding of the trust afforded to each robot a trust self-assessment three-item-scale validated by van Pinxteren et al. (2019) has been used (α = .838). Participants have been asked to imagine receiving advice from the robot they have seen in the video and to rate the extent to which they agreed or disagreed with three statements on a five points Likert scale (from *1- strongly disagree* to *5 -strongly agree*). The statements rated by participants were "I feel like the robot would have my best interest at heart", "I think that the robot would provide accurate information" and "I feel I could rely on the robot advice".

3.2.2 - Pre-test results

Participants in the pre-test have been 130, of which 26 have seen the video of Cruzr, 27 have seen the video of Asimo, 25 have seen the video of Kuri, 26 have seen the video of Sophia and 26 have seen the video of Pepper.

Reliability analysis for the scales used has been conducted. The scale for anthropomorphism has been proved to be reliable and its Cronbach's alpha was higher than the threshold of 0.7 (α =0.837). As a consequence, the variable ANTHR has been created as an average of the three items because the scale was proved to be mono-dimensional. The scale for cuteness has been proved to be reliable and its Cronbach's alpha was higher than the threshold of 0.7 (α =0.916). As a consequence, the variable CUTE has been created as an average of the three items because the scale was proved to be mono-dimensional. The scale for trust has not been proved to be reliable because its Cronbach's alpha was lower than the threshold of 0.7 (α =0.604). As a consequence, the variable TRUST has been created as an average of the three items but a different method for measuring trust has been implemented for the main study.

Table 1 shows descriptive statistics for Anthropomorphism (ANTHR), Cuteness (CUTE) and trust (TRUST).

Table 1 - Pre-test descriptive statistics

PRE - TEST DESCRIPTIVE STATISTICS			
Robot Design		ANTHR	CUTENESS
Cruzr	Mean	2.01	3.76
	N	26.00	26.00
	SD	0.82	1.58
Asimo	Mean	3.03	3.80
	N	27.00	27.00
	SD	0.91	1.77
Kuri	Mean	2.35	5.36
	N	25.00	25.00
	SD	0.87	1.42
Sophia	Mean	3.78	3.09
	N	26.00	26.00
	SD	0.88	1.62
Pepper	Mean	2.38	4.87
	N	26.00	26.00
	SD	1.04	1.34

To verify whether there was a difference among the five designs concerning the extent to which they were perceived by participants as different concerning the dimensions of anthropomorphism and cuteness one-way ANOVA has been conducted. It should be noted that for Asimo and Sophia cuteness was expected to act as a confounder in the sense that it was not expected to be significantly different from the control variable (Cruzr).

On the other hand, for Kuri anthropomorphism was expected to act as a confounder in the sense that it was not expected to be significantly different from the control variable (Cruzr). Pepper was expected to differ from the control variable (Cruzr) both concerning perceived anthropomorphism and cuteness.

Differences between groups have been significant for anthropomorphism ($F(4, 125) = 15.695$ $p < 0.05$) and cuteness ($F(4, 125) = 8.93$ $p < 0.05$). Moreover, Levine test for quality of variance was not significant so that we cannot reject the null hypothesis. This shows that variances between groups are different. For this reason, a Games-Howell post-hoc test has been run to see the difference between each design.

Participants who have seen Asimo ($M_{ANTHR} = 3.03$ $SD_{ANTHR} = 0.91$; $M_{CUTE} = 3.80$ $SD_{CUTE} = 1.77$) compared to participants who have seen the control condition i.e. Cruzr ($M_{ANTHR} = 2.01$ $SD_{ANTHR} = 0.82$; $M_{CUTE} = 3.76$ $SD_{CUTE} = 1.58$), demonstrated significant difference in anthropomorphism but not in cuteness, as expected.

Participants who have seen Kuri ($M_{ANTHR} = 2.35$ $SD_{ANTHR} = 0.87$; $M_{CUTE} = 5.36$ $SD_{CUTE} = 1.42$) compared to participants who have seen the control condition i.e. Cruzr ($M_{ANTHR} = 2.01$ $SD_{ANTHR} = 0.82$; $M_{CUTE} = 3.76$ $SD_{CUTE} = 1.58$), demonstrated significant difference in cuteness but not in anthropomorphism, as expected.

Participants who have seen Sophia ($M_{ANTHR} = 3.78$ $SD_{ANTHR} = 0.88$; $M_{CUTE} = 3.09$ $SD_{CUTE} = 1.62$) compared to participants who have seen the control condition i.e. Cruzr ($M_{ANTHR} = 2.01$ $SD_{ANTHR} = 0.82$; $M_{CUTE} = 3.76$ $SD_{CUTE} = 1.58$), demonstrated significant difference in anthropomorphism but not in cuteness, as expected.

Participants who have seen Pepper ($M_{ANTHR} = 2.38$ $SD_{ANTHR} = 1.04$; $M_{CUTE} = 4.87$ $SD_{CUTE} = 1.34$) compared to participants who have seen the control condition i.e. Cruzr ($M_{ANTHR} = 2.01$ $SD_{ANTHR} = 0.82$; $M_{CUTE} = 3.76$ $SD_{CUTE} = 1.58$), demonstrated no significant differences in both cuteness and anthropomorphism. Because Pepper was expected to elicit both perceptions of anthropomorphism and cuteness, but results have shown that it was not perceived as different concerning these dimensions, Pepper has been excluded from the main study.

Moreover, Games-Howell post-hoc test has shown a significant difference concerning perceptions of anthropomorphism between Asimo ($M_{ANTHR} = 3.03$ $SD_{ANTHR} = 0.91$) and Sophia ($M_{ANTHR} = 3.78$ $SD_{ANTHR} = 0.88$). This indicates that although Asimo and Sophia are both perceived as anthropomorphized with respect to the control condition, Sophia is perceived as more anthropomorphized with respect to Asimo.

In light of the results four robot designs have been selected Cruzr, Asimo, Kuri and Sophia. Cruzr has been selected as the control condition because it is not perceived as either anthropomorphised nor cute with respect to other designs. Asimo has been selected as moderately anthropomorphized condition (and not cute) because it is perceived as more anthropomorphized with respect to the control condition but less anthropomorphized with respect to Sophia. Kuri has been selected as the cute condition (not anthropomorphized) because it was perceived as cuter with respect to the control condition. Lastly, Sophia has been selected as extremely anthropomorphized condition (and not cute) because it was perceived as more anthropomorphized of both the control condition and the moderately anthropomorphized condition.

3.2.3 – Main study procedure

In this study, primary data have been collected through an online experiment conducted on Qualtrics. Because the study focused on the application of service robots to the beauty industry, the population of the study is made of women and experts of the beauty industry. As a consequence, the sample included women and man, the latter only if they worked in the beauty industry. The sample is a non-probabilistic quota sampling where quota was achieved when experts and non-experts reached a ratio of 1:5. The experiment's particular sampling procedure has been constrained by the particular lockdown conditions caused by the spread of Coronavirus SARS-CoV-2 (responsible for COVID-19) between March 2020 and May 2020. As a consequence, expert respondents have been collected online through social media groups of make-up experts and enthusiasts while the non-expert respondents have been collected on various social media groups.

Participants in the experiment have been asked to rate their expertise in the domain of make-up, to imagine to make a purchase situation, randomly saw one out of four videos tested in the pre-test (Cruzr, Asimo, Kuri and Sophia), received an advice, were asked to make a final decision and provided some demographics. Participants could choose to respond to the survey either in Italian or English. The following is a description of the survey procedure:

Independent variable: customer knowledge (CUST_KNOW). After a short introduction about the experiment participants have been asked to rate their expertise in the domain of make-up through a four-items-scale validated by Smith and Park (1992) (α =.80). Participants have been asked to rate the extent to which they agreed with four statements on a seven-points Likert scale (from *1- strongly disagree* to *7- strongly agree*). The four statements were "I feel very knowledgeable about make-up.", "If I had to purchase make-up today, I would need to gather very little information in order to make a decision.", "I feel very confident about my ability to tell the difference in quality among different make-up brands" and "If a friend asked me about make-up, I could give them advice about different brands."

Mediator: embarrassment (EMBARRAS). Participants have been asked to imagine that they had decided to buy a new foundation. They have been asked to think about how they would have felt in a situation in which they asked a shop assistant for advice. The anticipated embarrassment caused by this situation has been measured through a five-items-scale validated by Moore et al. (2006) (α =.91). Participants have been asked to rate on a seven points Likert scale the extent to which they thought thar they would have felt "embarrassed" (from *1- not embarrassed at all* to *7 – very embarrassed*), "self-conscious" (from *1- not self-conscious at all* to *7 – very self-conscious*), "awkward" (from *1- not awkward at all* to *7 – very awkward*), "uncomfortable" (from *1- not uncomfortable at all* to *7 – very uncomfortable*) and lastly "exposed" (from *1- not exposed at all* to *7 – very exposed*).

First choice. Subsequently, respondents have been asked to make their first decision. They have been shown a picture of an arm with 10 shades of foundation by Fenty Beauty (FentyBeauty.com). The arm presented 10 lines where the foundation had been applied, each one was labelled with the code of the foundation used (200, 210, …, 290)[9]. Participants have been asked to imagine that that was the result of them trying the foundation shades on their own arm and they have been asked to select one of the shades.

Robot design (DMY_ROB). After that, participants have been asked to imagine to be in a store where robots advised customers about their purchases and they have been randomly shown one out of four videos tested in the pre-test (Cruzr, Asimo, Kuri and Sophia). Each video has been assigned to a value. If the participant had seen Cruzr's video it has been coded as 0, if the participant had seen Asimo's video it has been coded as 1, if the participant had seen Kuri's video it has been coded as 2, if the participant had seen Sophia's video it has been coded as 3.

Advice. In the next section they were told that the robot had scanned their skin tone compared it with all the shades of foundation available in the shop, and, based on its algorithms, had advised them to choose the fourth shade, the one labelled 230. Participants were also shown a modified version of the previous picture that highlights the shade advised by the robot[10]. It should be noted that the shade advised by the robot is not random. Indeed, before designing the experiment, a make-up artist has been interviewed in order to provide accurate advice coming from a professional source.

Final choice. After that participants were asked to make a final decision and were shown again the image portrayed in appendix c, figure 1 - *Fondation shades – First choice and final choice* (FentyBeauty.com).

Robot anxiety (ROB_FEAR). In the next section their robot anxiety has been tested with a four-items-scale validated by Hinks (2020) has been adapted. The original scale by Hinks (2020) (α =.0.742) included a fifth item that has not been included because it referred to dangerous tasks performed by the robot which is not relevant to a context in which the robot task is advising customers. Participants have been asked to rate on a four points Likert (from *1- strongly disagree* to *4 -strongly agree*) scale the extent to which they agreed or disagreed with the statements "This robot is a good thing for society" and "This robot could steal people's jobs". Moreover, participants have been asked to rate their opinion of the robot on a four points Likert (from *1- very negative* to *4 -very positive*). Lastly, participants have been asked to rate how they would have felt if the robot assisted them on a four points Likert (from *1- very uncomfortable* to *4 -very comfortable*). The first, third and fourth items were reversed (by Hinks, 2020) and as a consequence their scoring have been inverted in the analysis.

Attention check and demographics. Subsequently participants have undergone an attention check verifying whether they remembered the advice they had received and provided some demographics. The demographics included age, nationality, field of occupation, gender, education and how often they use foundation.

[9] See appendix c, figure 1 - *Fondation shades – First choice and final choice* (FentyBeauty.com)
[10] See appendix c, figure 2 - *Fondation shades – Robot advice* (FentyBeauty.com)

Weight on advice (WOA). To measure the dependent variable, i.e. trust in robot and robot advice this work used the Weight On Advice (WOA), which is a variable used by Logg, Minson and Moore (2019) in their experiments on algorithm appreciation. Weight on advice is calculated as the difference between participant's initial choice and final choice, divided by the difference between initial choice and advice (Logg, Minson & Moore, 2019).

$$WOA_i = \frac{First\ Choice - Final\ Choice}{First\ Choice - Advice}$$

This variable is normally included between 0 and 1 where 0 indicates instances in which participants totally ignored the advice received while 1 indicates instances in which participants totally adjusted their decision to the advice received (Logg, Minson & Moore, 2019). Intermediate cases, i.e. instances in which individuals partially adjust their final decisions to the advice, score between 0 and 1. For instance, if a participant choses the shade 200 as her first choice and 220 as her final choice its WOA is (200- 220)/(200-230) = 0.67. Because accuracy of advice as well as witnessing algorithmic mistakes was proved to significantly alter WOA (Logg, Minson & Moore, 2019; Dietvorst, Simmons, & Massey, 2015), this study controlled for quality of the advice and did not provide feedback about accuracy of the advice following a technique already tested by (Logg, Minson & Moore, 2019). Advice provided in the main study was the same for each participant. As a consequence, differences in WOA do not depend on the advice itself or its accuracy (Logg, Minson & Moore, 2019).

The model proposed is a second stage conditional moderated mediation, that is a model in which the mediation effect is conditioned by a moderator (robot anxiety) which in turn is affected by a second moderator (robot design) (Hayes, 2017). Practically this is a mediation model with three two-ways interactions and one three-way interaction (Hayes, 2017). Therefore, the two regression formulas shown below developed by Hayes, (2017) formally represent this model:

$$\mathrm{M} = a_0 + a_1\mathrm{X} + \epsilon_1$$

$$\begin{aligned} Y = b_0 + b_1M + b_2W + b_3Z_1 + b_4Z_2 + b_5Z_3 + b_6MW + b_7MZ_1 + b_8MZ_2 \\ + b_9MZ_3 + b_{10}WZ_1 + b_{11}WZ_2 + b_{12}WZ_3 + b_{13}MWZ_1 + b_{14}MWZ_2 \\ + b_{15}MWZ_3 + c'X + \epsilon_2 \end{aligned}$$

Where

X= $CUST\_KNOW_i$

M= $EMBARRAS_i$

Y= WOA_i

$W = ROB\_FEAR_i$

Z_1= Asimo Z_2 = Kuri Z_3= Sophia

The reason why Z_0 i.e. Cruzr does not appear in the equation is that designs have been coded through dummy coding. Therefore, the effects can be interpreted with respect to Cruzr which is the control condition.

3.2.4 – Main study results

Reliability analysis for the scales used has been conducted. The scale for customer knowledge has been proved to be reliable and its Cronbach's alpha was higher than the threshold of 0.7 (α =0.844). As a consequence, the variable CUST_KNOW has been created as an average of the four items because the scale was proved to be mono-dimensional. The scale for embarrassment has been proved to be reliable and its Cronbach's alpha was higher than the threshold of 0.7 (α =0.934). As a consequence, the variable EMBARRAS has been created as an average of the five items because the scale was proved to be mono-dimensional. The scale for robot anxiety has been proved to be reliable and its Cronbach's alpha was higher than the threshold of 0.7 (α =0.736). As a consequence, the variable ROB_FEAR has been created as an average of the four items because the scale was proved to be mono-dimensional. All these variables have been standardized because robot anxiety is the result of four items measured with a four-points Likert scale while both customer knowledge and embarrassment are the results of respectively four and five items measured with a seven-points Likert scale. Through standardization each variable was recoded as having mean zero and standard deviation 1. Table 2a and 2b show descriptive statistics for the constructs of the model before standardization. It should be noted that the construct WOA has a lower number of observations and this is due to the lack of those respondents who initially chose the shade advised by the robot and did not change their decision in their final choice and were cancelled out from the regression analysis through listwise relation, which happened with 74 respondents. The means of WOA are very similar across groups. Moreover, the mean is around 0.5 and this is caused by the fact that the scoring of this variable is very polarized around the extreme values of 0 and 1 and their distribution is not normal[11]. Moreover, embarrassment's skewness shows that the distribution of the variable is asymmetrical and left skewed[12]. This problem has been addressed in the regression analysis performing bootstrap.

Table 2.a - Main study variables descriptive statistics

VARIABLES DESCRIPTIVE STATISTICS					
	N	Mean	SD	Skewness	Kurtosis
CUST_KNOW	365	3.9589	1.45244	0.048	-0.687
EMBARRAS	365	2.1321	1.40292	1.256	0.668

[11] See appendix d, the figure 4 - *WOA distribution*
[12] See appendix d, figure 2- *Embarrassment distribution*

ROB_FEAR	365	2.6110	0.61852	0.232	-0.233
WOA	291	0.5451	0.49735	-0.237	-1.855

Table 2.b - Main study WOA and Robot anxiety between groups descriptive statistics

WOA AND ROBOT ANXIETY DESCRIPTIVE STATISTICS BETWEEN GROUPS						
		N	Mean	SD	Min.	Max.
WOA	Cruzr	73	0.5114	0.50409	-0.50	1.00
	Asimo	72	0.5567	0.49761	-0.33	1.00
	Kuri	73	0.5532	0.48910	0.00	1.00
	Sophia	73	0.5594	0.50718	-0.50	1.00
ROB_FEAR	Cruzr	93	2.5699	0.58673	1.50	4.00
	Asimo	84	2.4940	0.56635	1.25	4.00
	Kuri	96	2.5339	0.57768	1.25	4.00
	Sophia	92	2.8397	0.68398	1.00	4.00

Participants who have taken part in the study have been 373. However, 8 have been deleted because they failed the attention check, therefore participants analysed in the main study have been 365. Of the 365, 93 participants have seen the control condition (Cruzr), 84 participants have seen the moderately anthropomorphized condition (Asimo), 96 participants have seen the cute condition (Kuri) and 92 participants have seen the extremely anthropomorphized condition (Sophia). Because 74 participants selected as their first choice the same foundation shade that was subsequently advised by the robot, they have not been considered in the weight on advice variable. As a consequence, among participants counted in the WOA variable 73 have been exposed to the control condition, 72 have been exposed to the moderately anthropomorphized condition, 73 have been exposed to the cute condition and 73 have been exposed to the extremely anthropomorphized condition. Tables 1-5 in appendix E show descriptive statistics for gender, job, education, foundation usage and age. Because the target market of foundation is mainly women, participants' responses have been considered only if the participant was a woman, or, if the participant was a man, he was only included in the sample if he stated that he was employed in the beauty industry and an expert about make-up. As a consequence, 99.2% of the sample was made of women[13]. For what concern participants' occupation, 3.6% worked in the beauty industry, 20.5% worked in a different industry, 71.5% were students, 0.5% were retired and 3.8% were unemployed[14]. Concerning the level of education of the sample the majority reported as the highest level of education achieved to be bachelor (43% of the sample), followed by high school (37% of the sample), master (18.9% of the sample) and PhD (0.3% of the sample)[15]. Concerning foundation usage, the frequency of answers in the

[13] See see appendix e, table 1 - *Gender frequency statistics*
[14] See appendix e, table 2 - *Job frequency statistics*
[15] See appendix e, table 3 - *Education frequency statistics*

sample exhibited a u-shape suggesting that respondents either use foundation always and nearly always (54% of respondents) or never and nearly never (34.8% of respondents)[16]. The age of the sample ranged between 17 and 65 and its mean was almost 26 years old[17].

An interesting finding about participants' choices in the experiment is visible from figure 1- *percentage of right answers in first and final choice*. The graph represents the percentage of experts (i.e. participants whose customer knowledge was equal or higher than 5.5/7) and novices (i.e. participants whose customer knowledge was lower than 5.5/7) who selected the foundation shade 230 before and after receiving the advice. This shade is considered as the correct, or standard answer in this study because it is the one that a professional make-up artist would have recommended for that particular skin tone. In the graph it is possible to see that, before receiving the advice, experts selected the correct shade more often than novices. Indeed 19.8% novices selected the right answer as their first choice while 22.39% of experts selected the right answer as their first choice. However, after receiving advice the trend changes. In fact, although the percentage of right answers in the final choice are higher for both groups, novices selected the right choice more often than experts. Indeed 63.42% novices selected the right answer as their final choice while 53.73% of experts selected the right answer as their final choice. This bears two implications: First, novices in the sample listened to robot advice more than experts did, in line with our first hypothesis; secondly, accuracy of customer groups (novices and experts) dramatically changes after receiving advice. Indeed, while experts outperformed novices before receiving advice, novices managed to relatively outperform experts integrating robot advice.

[16] See appendix e, table 4 – *Foundation usage frequency statistics*
[17] See appendix e, table 5 – *Age descriptive statistics*

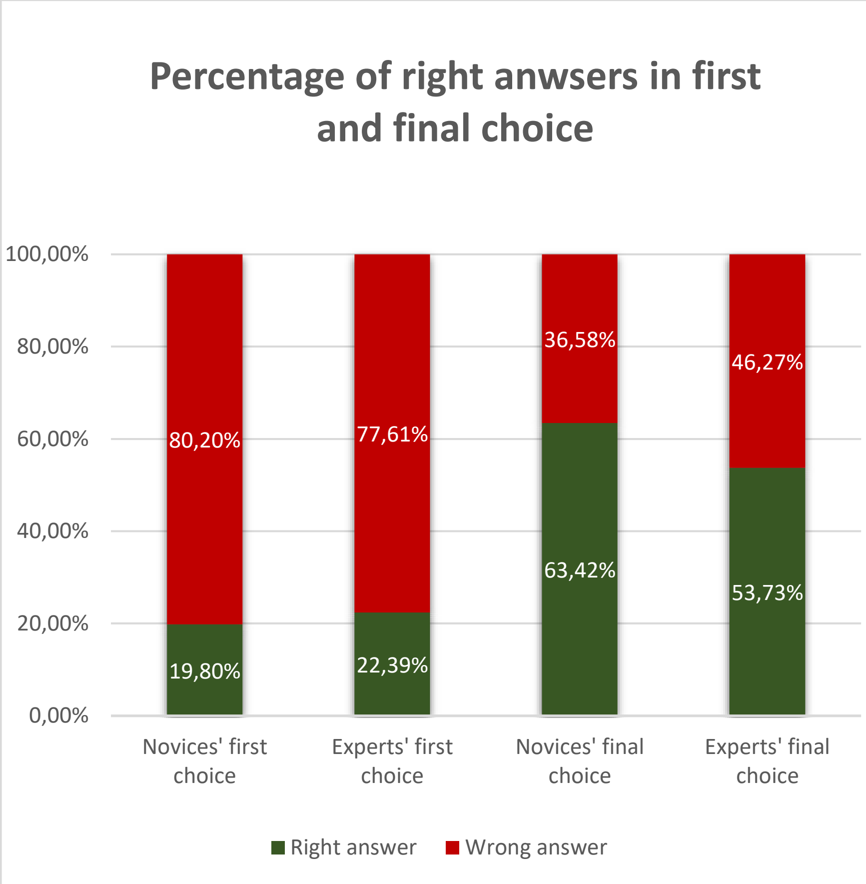


Figure 1- Percentage of right answers in first and final choice

A second stage conditional moderated mediation analysis has been conducted using PROCESS v3.4. model 18 with bootstrap 10000 (Hayes, 2017).

Table three shows that the model fits the data. The model of the effect of customer knowledge on embarrassment shows a poor fit (R^2 = 0.0702) this means that the model explains 7% of the variance. The F statistics F (289, 1) = 20.975 p<0.05 indicates that the model fits the data. The model that shows the effect of customer knowledge, embarrassment, robot anxiety, robot designs and their interactions show a poor fit (R^2 = 0.1576) this means that the model explains 16% of the variance. The F statistics F (274, 16) = 5.7004 p<0.05 indicates that the model fits the data.

Table 3- Main study model fit

OUTCOME VARIABLE: EMBARRAS					
Model Summary	R-sq	F	df1	df2	p
	0.0702	209.749	1	289	0.0000
OUTCOME VARIABLE: WOA					
Model Summary	R-sq	F	df1	df2	p
	0 .3969	5.704	16	274	0.0000

Recall that the first hypothesis this model is supposed to test was that customer knowledge negatively affects weight on robot advice. In other words, novices as opposed to experts were expected to rely more on robot advice and exhibit higher levels of weight on advice.

H1: Novices (experts) of a specific product or service domain are more (less) likely to trust robot advice

This hypothesis represents what is usually called *path c* i.e. the total effect without mediation of the independent variable on the dependent variable. To test this hypothesis a simple linear regression has been run and the results have confirmed that customer knowledge has a negative and significant effect on weight on advice. There are no problems of multicollinearity as it is visible from the VIF < 3. The model fit F (289, 1) = 8.428 p<0.05 indicates that the model fits the data. The effect of customer knowledge on weight on advice is negative and significant (β = -0.084, t = -2.903 p < 0.05) hence H1 is confirmed.

Table 4 – Main study total effect

DEPENDENT VARIABLE : WOA				
	B	t	Sign.	VIF
Constant	0.542	18.824	0.000	
Customer Knowledge	-0.084	-2.903	0.004	1.000

The second hypothesis of this model was that customer knowledge negatively influences anticipated embarrassment. In other words, novices, as opposed to experts, were expected to report higher levels of anticipated embarrassment.

H2 Novices (experts) of a specific product or service domain are more (less) likely to experience embarrassment due to lack of customer knowledge

This hypothesis represents what is usually called *path a*, i.e. the effect of the independent variable on the mediator. Results of table five confirmed a negative and significant effect of customer knowledge on embarrassment (β = -0.265, t = -4.580 p < 0.05) as a consequence, hypothesis 2 is confirmed[18].

Table 5 – Main study model estimation

OUTCOME VARIABLE : EMBARRAS - REGRESSION MODEL					
	coeff	t	p	LLCI	ULCI
constant	0.0011	0.0195	0.984	-0.109	0.111
CUST_KNOW	-0.265	-4.580	0.000	-0.379	-0.151

The third hypothesis of this model was that anticipated embarrassment positively influenced weight on advice. In other words, respondents reporting higher levels of embarrassment, as opposed to respondents reporting

[18] See appendix f, table 1 – *bootstrap results*

lower levels of embarrassment, were expected to rely more on robot advice and report higher levels of weight on advice.

H3 higher levels of embarrassment lead to higher trust in robot advice

This hypothesis represents what is usually called *path b*, i.e. the effect of the mediator on the dependent variable. Results of table six confirmed a positive and significant effect of embarrassment on weight on advice ($\beta = 0.105$, $t = 2.3662$ $p < 0.05$) (see table 6) as a consequence hypothesis 3 is confirmed. For further information[19].

The fourth hypothesis of this model was that robot anxiety reduces the effect of embarrassment on weight on advice. In other words, holding the level of embarrassment equal, respondents reporting higher levels of robot anxiety, as opposed to respondents reporting lower levels of robot anxiety, were expected to rely less on robot advice and report lower levels of weight on advice.

H4 robot anxiety decreases the effect of embarrassment on trust in robot

This hypothesis represents the moderation effect on path b, i.e. the effect of the moderator on the effect of the mediator on the dependent variable. Results of table six confirmed a negative and significant effect of the interaction of embarrassment and robot anxiety (Int 1) on weight on advice ($\beta = -0.0922$, $t = -2.025$ $p < 0.05$) (see table 6) as a consequence hypothesis 4 is confirmed. For further information see appendix f, table 1 – *bootstrap results*.

Because *path a* (the negative effect of customer knowledge on embarrassment) and *path b* (the positive effect of embarrassment on weight on advice) have been proved to be significant, the possibility that there was a mediation effect has been verified. The indirect effect of customer knowledge on weight on advice via embarrassment – i.e. path a*path b – varies with the level of robot anxiety confirming the moderated mediation proposed by the model. For low levels of robot fear (-0.9878) $\beta = -0.052$, $p < 0.05$, for medium levels of robot fear (- 0.194) $\beta = -0.032$, $p < 0.05$, the effect is significant, while for high level of robot fear it is not[19] Moreover, the direct effect of customer knowledge on WOA which is usually called *path c'*, is negative and significant ($\beta = -0.007$, $t = -2.380$ $p < 0.05$) (see table 6). This further confirms the first hypothesis of this model because customer knowledge negatively affects trust in robot even without the mediation of embarrassment. Therefore, we discover a partial conditional mediation of customer knowledge on weight on advice via embarrassment depending on the level of robot anxiety. This means that the effect of customer knowledge on WOA is partially mediated by anticipated embarrassment. Moreover, robot anxiety moderates the effect of embarrassment on WOA. In other words, customer knowledge negatively influences embarrassment which positively influences weight on advice. However, when individuals are afraid of the robot, the positive effect of embarrassment on WOA decreases significantly.

[19] See appendix f, table 1 – *bootstrap results*

Table 6 – Main study model estimation

OUTCOME VARIABLE : WOA - REGRESSION MODEL					
	coeff	t	p	LLCI	ULCI
constant	0.4834	86063	0.000	0.3728	0.594
CUST_KNOW	-0.0684	-23804	0.018	-0.125	-0.0118
EMBARRAS	0.105	2.3662	0.0187	0.0176	0.1923
ROB_FEAR	-0.1238	-1.9602	0.051	-0.2481	0.0005
Int_1	-0.0922	-2.025	0.0438	-0.1818	-0.0026
Asimo	0.0404	0.5046	0.6142	-0.1173	0.1981
Kuri	0.0345	0.4485	0.6541	-0.117	0.1861
Sophia	0.1253	1.5916	0.1126	-0.0297	0.2803
Int_2	-0.0564	-0.6892	0.4913	-0.2176	0.1048
Int_3	-0.2006	-3.0469	0.0025	-0.3302	-0.071
Int_4	0.0249	0.3663	0.7144	-0.1091	0.1589
Int_5	-0.0581	-0.6562	0.5122	-0.2325	0.1163
Int_6	0.0017	0.0214	0.983	-0.1587	0.1622
Int_7	0.0091	0.1155	0.9082	-0.1453	0.1634
Int_8	0.0744	0.8065	0.4206	-0.1071	0.2559
Int_9	0.0193	0.3269	0.744	-0.097	0.1356
Int_10	0.0782	1.2306	0.2195	-0.0469	0.2033
PRODUCT TERMS KEY:					
Int_1 :	EMBARRAS	x	ROB_FEAR		
Int_2 :	EMBARRAS	x	Asimo		
Int_3 :	EMBARRAS	x	Kuri		
Int_4 :	EMBARRAS	x	Sophia		
Int_5 :	ROB_FEAR	x	Asimo		
Int_6 :	ROB_FEAR	x	Kuri		
Int_7 :	ROB_FEAR	x	Sophia		
Int_8 :	EMBARRAS	x	ROB_FEAR	x	Asimo
Int_9 :	EMBARRAS	x	ROB_FEAR	x	Kuri
Int_10 :	EMBARRAS	x	ROB_FEAR	x	Sophia

The fifth hypothesis of this model concerned the effect of anthropomorphized designs on robot anxiety and it was divided in two sub hypotheses, respectively hypothesis 5a and hypothesis 5b. Hypothesis 5a was that moderately anthropomorphized designs reduce robot anxiety. In other words, respondents exposed to the moderately anthropomorphized design condition (Asimo), as opposed to respondents exposed to the control design condition (Cruzr), were expected to exhibit lower levels of robot anxiety.

H5a When the robot possesses a moderately anthropomorphized (mechanized) design, people experience low (high) robot anxiety

Hypothesis 5b was that extremely anthropomorphized designs increase robot anxiety. In other words, respondents exposed to the extremely anthropomorphized design condition (Sophia), as opposed to respondents exposed to the control design condition (Cruzr), were expected to exhibit higher levels of robot anxiety.

H5b When the robot possesses an extremely (moderately) anthropomorphized design, people experience high (low) robot anxiety

The sixth hypothesis of this model concerned the effect of cute designs on robot anxiety. In particular, according to this hypothesis, cute design was expected to reduce robot anxiety. In other words, respondents exposed to the cute design condition (Kuri), as opposed to respondents exposed to the control design condition (Cruzr), were expected to exhibit lower levels of robot anxiety.

H6 When the robot possesses a cute (non-cute) design people experience low (high) robot anxiety

To test for these hypotheses and verify whether there was a difference among the four designs concerning the extent to which they elicited different levels of robot anxiety in participants, one-way ANOVA has been conducted. Differences between groups have been significant for robot anxiety ($F (3, 361) = 6.071$ $p< 0.05$). Moreover, Levene test for equality of variance was not significant so that the null hypothesis cannot be rejected. This shows that variances between groups are different. For this reason, a Games-Howell post-hoc test has been run to see the difference between each design (See table 7a – *Main study robot design- robot anxiety descriptive statistics* and table 7b – *Main study robot design – robot anxiety post hoc analysis*) .

Participants who have seen Asimo ($M = -0.189$ $SD = 0.916$) compared to participants who have seen the control condition i.e. Cruzr ($M = -0.664$ $SD = 0.949$), exhibited a robot anxiety mean difference between groups of 0.123 ($Mean_{Cruzr} - Mean_{Asimo} = 0.123$) which was not significant, hence hypothesis 5a has not been confirmed. Moreover, as it is shown in table 6, when looking at the interaction of this particular design (with respect to the control condition) with robot anxiety and embarrassment, the effect of this design is positive but not significant ($\beta = 0.074$, $t = 0.806$ $p = 0.42$).

Participants who have seen Sophia ($M = 0.370$ $SD = 1.106$) compared to participants who have seen the control condition i.e. Cruzr ($M = -0.664$ $SD = 0.949$), exhibited a robot anxiety mean difference between groups of -0.436 ($Mean_{Cruzr} – Mean_{Sophia} = -0.436$) which was significant, hence hypothesis 5b has been confirmed. However, as it is shown in table 6, when looking the interaction of this particular design (with respect to the control condition) with robot anxiety and embarrassment the effect of this design is positive but not significant ($\beta = 0.078$, $t = 1.231$ $p = 0.22$).

Participants who have seen Kuri ($M = -0.123$ $SD = 0.934$) compared to participants who have seen the control condition i.e. Cruzr ($M = -0.664$ $SD = 0.949$), exhibited a robot anxiety mean difference between groups of 0.058 ($Mean_{Cruzr} - Mean_{Asimo} = 0.058$) which was not significant, hence hypothesis 6 has not been confirmed. Moreover, as it is shown in table 6, when looking the interaction of this particular design (with respect to the control condition) with robot anxiety and embarrassment the effect of this design is positive but not significant (β = 0.019, t = 0.327 p = 0.744).

Table 7a – Main study robot design – robot anxiety descriptive statistics

ROBOT ANXIETY DESCRIPTIVE STATISTICS			
	N	Mean	SD.
Cruzr	93	-0.066	0.948
Asimo	84	-0,189	0.916
Kuri	96	-0,125	0.934
Sophia	92	0,370	1.106
Total	365	0.000	1

Table 7b – Main study robot design –robot anxiety post-hoc analysis

ROBOT DESIGN - ROBOT ANXIETY GAMES - HOWELL POST HOC ANALYSIS			
(I) Robot design	(J) Robot design	Mean difference (I-J)	Sign.
Cruzr	Asimo	0.123	0.818
	Kuri	0.058	0.974
	Sophia	-0.436*	0.023
Asimo	Cruzr	-0.123	0.818
	Kuri	-0.064	0.966
	Sophia	-.559*	0.002
Kuri	Cruzr	-0.058	0.974
	Asimo	0.064	0.966
	Sophia	-.495*	0.006
Sophia	Cruzr	.436*	0.023
	Asimo	.559*	0.002
	Kuri	.494*	0.006

*. Mean difference is significant at the 0.05 level

3.3 – DISCUSSION

The focus of this research is to investigate whether customer knowledge can be used as an effective behavioural segmentation variable for the identification of target customers more likely to rely on robot advice. In addition to that, this research investigates the role of robot anxiety on reliance on robot advice and the extent to which different designs moderate robot anxiety. In particular, this study predicts that novices, as opposed to experts, are more likely to rely on robot advice and that this happens because lack of product or service knowledge triggers anticipation of embarrassment which spurs people to avoid human interactions to preserve their self-image. In other words, customer knowledge is expected to negatively influence anticipated embarrassment and weight on robot advice because as customer knowledge increases, individuals are less likely to anticipate embarrassment in the service encounter and they are less willing to rely on robot advice. On the other hand, anticipated embarrassment in the service encounter is expected to positively affect trust in robot and reliance to its advice as a result of a coping behaviour for human interaction avoidance. The rationale behind this is based on Miller's (1996) findings since he proved that lack of customer knowledge positively influences perceived and anticipated embarrassment. Moreover, Grace (2007) and Londono, Davies and Elms (2017) demonstrated that embarrassment positively influence social interaction avoidance.

Furthermore, this study predicts that when people are uncomfortable in human-robot interactions due to robot anxiety, they are less likely to trust the robot and rely on its advice. This reasoning is based on the fact that prior literature on robot anxiety demonstrated that this fear causes human-robot interaction avoidance and it decreases trust in the robot (Nomura et al. 2006; de Graaf & Allouch, 2013; Mende et al. 2019; Mori, 1970; Mori, MacDorman, & Kageki, 2012; Mathur & Reichling, 2016). As a consequence, the positive effect of embarrassment on reliance to robot advice is expected to be lower when people experience robot anxiety. Furthermore, this study predicts that robot design influences the extent to which people fear robots. In particular, people exposed to moderately anthropomorphised designs are expected to experience fewer anxiety, people exposed to extremely anthropomorphized designs are expected to experience greater robot anxiety and people exposed to cute designs are expected to experience fewer robot anxiety. These hypotheses are based on the uncanny valley effect discovered by Mori (1970) which predicts higher liking for anthropomorphized designs with respect to non anthropomorphized designs (Mori, 1970; Mori, MacDorman, & Kageki, 2012), however, when the robot looks almost perfectly like a human being, Mathur & Reichling (2016) demonstrated that people experience a sense of uncanniness and this effect influences trust in robot. Moreover, cuteness in robot design was expected to decrease perceived threat stemming from the robot (Nenkov & Scott, 2014; Caudwell, Lacey, & Sandoval, 2019) and thus decrease fear of the robot. Prior literature on cute design demonstrated that cute design trigger associations with naïve and vulnerable creature decreasing perceived threat of robots (Nenkov & Scott, 2014; Caudwell, Lacey, & Sandoval, 2019). This is expected to be reflected by lower fear of service robots perceived as cute and to increase trust afforded to such robots.

Results of the experiment conducted confirm the negative significant effect of customer knowledge on weight on advice which implies that novices are more likely to integrate robot advice in their decision making. This confirms the first hypothesis of this study and it proves that customer knowledge is an appropriate behavioural segmentation variable for the effective implementation of service robot counselling in the service encounter context because novices are willing to rely on service robot advice. This finding is in line with literature findings about algorithm appreciation (Logg, Minson & Moore, 2019) and algorithm aversion (Dietvorst, Simmons, & Massey, 2015). The underlying principle explaining this effect could be the relation between task's perceived difficulty and reliance on advice discovered by Gino and Moore (2006). When people perceive a certain task as difficult, they are more prone to seek for advice and integrate it (Gino & Moore, 2006). Alba and Hutcherson (1987) proved that when people develop expertise in a specific domain they improve and strengthen a set of cognitive tools needed for performance of tasks in that specific domain. As a consequence, experts develop a superior effectiveness and efficiency of decision making with respect to novices and this provokes a feeling called cognitive ease (Kahneman, 2011; Park & Lessing 1981). According to Kahneman (2011) this sensation provokes a perception of effortlessness of the task. As a consequence, novices, who are less likely to experience cognitive ease with respect to experts, may be more likely to rely on advice because they are more likely to perceive a task related to the service as complex.

In this regard, this study demonstrates an important finding concerning advice taking and accuracy of decision making. In fact, comparing the answers of novices and experts before and after receiving advice, it is clear that experts outperform novices before receiving advice in terms of accuracy of decision-making. As it was mentioned above, in this study correct answer was shade 230 which, according to a make-up artist interviewed before designing the experiment, is the correct shade for matching the skin tone displayed in the pictures[20]. Before receiving advice, experts' ratio of correct answers is higher with respect to novices' ratio of correct answers. This is not surprising since prior literature demonstrated how superior expertise improves accuracy of decision-making because experts develop certain skills that facilitate and improve accuracy of decision-making (Alba & Hutcherson, 1987; Kahneman, 2011; Park & Lessing 1981). However, after participants receive robot advice, the situation changes dramatically. Indeed, after receiving the advice, novices' ratio of correct answers is higher with respect to experts' ratio of correct answers. This seemingly counterintuitive finding was previously demonstrated by Logg, Minson and Moore (2019) in the context of algorithm advice in a study investigating *algorithm appreciation*. According to Logg, Minson and Moore (2019) the reason for this effect is attributable to experts' overconfidence which leads them to experience what Dietvorst, Simmons and Massey (2015) termed as *algorithm aversion*. In fact, experts' tendency to overestimate their own judgement results in lower advice taking (Logg, Minson & Moore, 2019). This is true both when the advice comes from a human and an algorithm-based source (Dietvorst, Simmons, & Massey, 2015; Dawes, 1979;

[20]See appendix c, figure 1 - *Fondation shades – First choice and final choice* (FentyBeauty.com) and figure 2 - *Fondation shades – Robot advice* (FentyBeauty.com)

Dawes, Faust & Meehl, 1989; Yeomans et al. 2019). Thus, overconfidence is a key element explaining advice discounting (Logg, Minson & Moore, 2019; Healy & Moore, 2007). An explanation for novices' lower overconfidence can be attributed to higher perceived difficulty of the task which was proved by Gino and Moore (2006) to reduce overconfidence. However, not only novices have a higher tendency to integrate robot advice. This also influences accuracy of decision making such that novices manage to outperform experts' decision-making accuracy through their greater integration of robot advice. Similar results had been found by Logg, Minson and Moore (2019) in specific domains such as politics, economics, and law. However, this research demonstrates that the occurrence of this phenomenon is relevant also in consumer contexts.

Moreover, this research proves that there is also another element playing a key role in shaping the negative relation between customer knowledge and weight on advice: anticipated embarrassment. The experiment conducted in this research proves that the effect of customer knowledge on weight on advice is conditionally mediated by anticipated embarrassment in the service encounter context. In fact, the experiment proved that customer knowledge significantly and negatively influences embarrassment and that embarrassment positively affects weight on robot advice such that part of the effect of customer knowledge on trust in robot advice is explained by an increase in anticipated embarrassment which increases reliance on robot advice. Moreover, this study proved that this effect is conditioned by robot anxiety, which decreases the effect of embarrassment on weight on advice. The fact that novices are more likely to experience and anticipate embarrassment in the service encounter context confirms the second hypothesis of this model and it is in line with findings of Miller (1996) who found a positive correlation between lack of knowledge and increased anticipation and perception of embarrassment.

Furthermore, the positive relation between anticipated embarrassment and weight on robot advice proved in this study confirms the third hypothesis of the model. This relation can be explained through a coping behaviour aimed at protecting individuals' self-image when they believe that it is at stake because of their lack of familiarity with the service or product. Baumeister et al. (2001) demonstrated that embarrassment is highly influential in shaping individuals' behaviour because people are highly motivated to preserve the usual image that they present of their self. Moreover, Grace (2007) empirically proved that avoidance of social interaction is a coping behaviour enacted in the service encounter. In fact, according to Miller (1996) a prerequisite for people to perceive and anticipate embarrassment is that they fear that other people they are interacting with (either directly or indirectly) may negatively evaluate them. Robot advisors, although able to create some kind of social presence (Mann et al. 2015; Wirtz et al, 2018), are unlikely to be perceived as conscious agents able to negatively evaluate customers (Gray, Gray & Wegner, 2007) and thus they are less likely to trigger embarrassment. As a consequence, a further explanation for novices' tendency to rely on algorithm-based advice and, in particular, robot advice, is attributable to a coping behaviour triggered by a desire to avoid social interactions. This is caused by anticipated embarrassment in the service encounter due to their lack of expertise and familiarity the product or service.

However, this study demonstrated that the extent to which embarrassment increases weight on robot advice depends on the extent to which people experience or anticipate robot anxiety in human-robot interactions. When people experience robot anxiety, the effect of embarrassment on weight on advice is dramatically reduced and this finding confirms the fourth hypothesis of this model. An explanation for this effect is that robot anxiety triggers a series of negative feelings and attitudes towards robots as well as an anxious state that spurs people to avoid robots and human-robot-interactions (de Graaf & Allouch, 2013). This fear and a sense of uncanniness were proved to have a negative influence on trust afforded to robots (Mathur & Reichling, 2016). Therefore, the reason for this effect can be attributed to a desire for robot-avoidance triggered by the fear and discomfort caused by the idea of interacting with the robot.

The last part of the model concerned the moderation of robot design of the moderation effect of robot anxiety on the mediation effect of embarrassment of the relation between customer knowledge and weight on the advice. In particular, the model of the study predicted that three types of designs moderated robot anxiety. The moderately anthropomorphized design was expected to decrease robot anxiety compared to the control condition (hypothesis 5a), the extremely anthropomorphized design was expected to increase robot anxiety (hypothesis 5b) and the cute design was expected to decrease robot anxiety (hypothesis 6). This study only confirms these hypotheses partially. Hypothesis 5a is not confirmed because the moderately anthropomorphized design did not exhibit substantial differences in terms of robot anxiety with respect to the control condition. Indeed, participants exposed to this condition as opposed to participants exposed to the control condition did experience slightly lower levels of robot anxiety, however this difference was not significant. When looking at the interaction between the effect of this design on the moderated mediation of the model the effect is positive as predicted but it is not significant. The very same pattern can be observed for the cute design which means that hypothesis 6 is not confirmed either. An explanation for these inconclusive results could be due to an effect discovered by Savela, Turja and Oksanen (2017) according to which participants in experiments overestimate the robot anxiety that they would experience in human-robot interactions. Indeed, participants that actually interact with a physical robot tend to report significantly lower levels of robot anxiety with respect to participants asked to imagine interacting with a robot. Looking at the average robot anxiety reported by the sample it is clear that most people were severely afraid of the robots regardless of their design. For practical reasons and the spread of SARS-CoV-2 (responsible for COVID-19) it was impossible to conduct this experiment with physically present participants and robots. However, it is possible that conducting the experiment online may have intensified anticipation of robot anxiety leading to biased results.

Moreover, because participants only had the possibility to see a short video of the robot rather than personally seeing it interacting with the surrounding environment, they may have not been able to fully appreciate the details of the robot nor they could engage with it. De facto Kuri is only 50 cm tall (Mayfield Robotics, 2020) while Cruzr is 1.5 m tall (UBTECH Robotics, 2020). These characteristics were proved to have a dramatic effect on perceived threat of the robot and consequent robot anxiety (Broadbent, 2017). However, because participants could only see a video of one robot, features such as body size may have gone unnoticed.

Another element that might have prevented these designs from effectively diminishing robot anxiety is the fact that the majority of the sample was made of women and women were proved to exhibit significantly higher levels of robot anxiety with respect to men by Reich and Eyssel (2013). Target customers of make-up and foundation are typically women, as a consequence the online experiment has been mostly distributed among women. However, because they tend to be more afraid of robots, it is possible that robot design did not manage to reduce such high levels of robot anxiety.

Another explanation could be related to the fact that robots shown may have not been perceived as different enough to justify different levels of robot anxiety. The pre-test of this study did demonstrate that these robots were perceived as expected, thus Kuri has been perceived as significantly cuter than Cruzr and Asimo has been perceived as significantly more anthropomorphized with respect to Cruzr. However, these differences may not have been great enough to change participants attitude towards Cruzr, Asimo and Kuri.

The only design that was proved to elicit a significant different level of robot anxiety was the extremely anthropomorphized one. Indeed, people exposed to the extremely anthropomorphized design exhibited significantly higher levels of robot anxiety confirming hypothesis 5b. However, when looking at the interactions between the effect of robot designs, robot anxiety and embarrassment on WOA the results are not significant. This means that extremely anthropomorphized designs do elicit higher levels of robot anxiety, however this effect is not substantial enough to influence weight on advice. The explanation for the increased robot anxiety generated by this kind of design is attributable to the *uncanny valley effect* according to which people have a preference for anthropomorphized design but they find extremely anthropomorphized designs to be creepy and this negatively affects trust afforded to such robots (Mori, 1970; Mori, MacDorman, & Kageki, 2012). However, because people could only see a video of the robot rather than physically interacting with it, they might have not felt engaged enough with it. It is possible that this inhibited the extent to which this kind of robot design has been influential in shaping trust in robot advice.

An interesting unexpected finding that has a considerable effect on weight on advice is the interaction between embarrassment and the cute design which has a negative influence on weight on advice. What is extremely interesting about this finding is that when looking for separate influences on weight on advice of these two variables they are both positive. However, when combined, they negatively and significantly influence trust granted to the robot. It makes sense to think that the cute design could be construed as incompetent due to its resemblance to a toy or a naïve creature. In fact, cute design in service robots was proved to increase warmth of the machine due to the resemblance to kids (Nenkov & Scott, 2014 ; Caudwell, Lacey, & Sandoval, 2019), however, this may come at the expense of competence according to the *stereotype content model* (Fiske, Cuddy & Glick, 2007). This study demonstrated that people that experience and anticipate embarrassment the most in the service encounter are the ones unfamiliar with the product or service. As a consequence, it is possible that those people require the advisor to be or at least appear to be competent enough to guide their decision. It is possible that cute designs, or simply the cute design used in the experiment, do not convey such competence. the fact that the robot does not talk might have made people think that robot was going to be of little help in the service encounter. Another explanation comes from Caudwell, Lacey, and Sandoval (2019). In fact, in a work assessing the effect of cute designs on people's attitude towards robots they found that, in general, cute designs foster acceptance of robots because they increase engagement with the robot and the extent to which people are willing to interact with them (Caudwell, Lacey, & Sandoval, 2019). However, in instances in which cuteness of the design is perceived as irrelevant, cuteness may even be detrimental to positive attitudes towards the robot (Caudwell, Lacey, & Sandoval, 2019). It is possible that people anticipating embarrassment in the service encounter may perceive cuteness of the service robot as irrelevant because what they really seek for in an advisor is competence. Thus, this would explain why the combination of embarrassment and cute design does not work well for people anticipating embarrassment while the design itself does not negatively affect weight on advice.

3.3.1 - Theoretical contribution

This research contributes to existing literature in numerous ways. *Firstly*, it contributes to the literature on advice taking, judge-advisor systems and weight on algorithmic advice (Dawes, 1979; Dawes, Faust & Meehl, 1989; Yeomans et al. 2019; Buell & Norton, 2011) showing that effects comparable to the ones elicited by algorithms can be triggered by service robots. *Secondly*, this work shows that findings about algorithm aversion (Dietvorst, Simmons, & Massey, 2015) and appreciation (Logg, Minson & Moore, 2019) apply to service robots as well, confirming that while novices exhibit higher reliance on algorithmic advice – whether the source is a physical robot or an virtual algorithm – experts exhibit lower reliance on algorithmic advice. *Thirdly*, this research shed a light on motivation for novices' higher increased reliance on algorithmic advice in the service encounter context that has never been investigated before. De facto, prior literature has identified experts' overconfidence to be the main determinant for such effect (Logg, Minson & Moore, 2019; Healy & Moore, 2007). However, this research proved that the conditional mediation of embarrassment of customer knowledge on WOA contributes to explain novices' greater weight on advice with respect to experts. *Fourthly*, this study contributes to literature on embarrassment (Grace, 2007; Dahl, Manchanda & Argo, 2001) by identifying a new coping behaviour to avoid anticipated embarrassment: higher reliance on technology-based self-service in the form of service robots. This not only expands insights about consequences and determinants of embarrassment and anticipated embarrassment, but it also allows for a deeper understanding of how such factors facilitate acceptance of service robots. *Fifthly*, this research proves that findings about embarrassment caused by the purchase of embarrassing products or service developed by Londono, Davies and Elms (2017) are applicable to instances in which embarrassment stems from perceptions of lack of knowledge of the product or service and thus it extends such findings to a broader variety of products and services. *Sixthly*, the findings of this study expand literature about trust in robots and it achieves that through a method that had only been implemented for measuring reliance trust in algorithm, i.e. weight on advice. The application of JAS system as well as weight on advice in the context of robot trust could deepen our understanding of what factors are key determinants in robot trust which have been proved to be crucial in affecting service robot acceptance (van Pinxteren et al. 2019). *Seventhly*, this research contributes to the understanding of the role of robot anxiety in diminishing trust in robot. In particular, it shows that robot anxiety can seriously harm efficacy of service robots through the diminishment of the positive relation between anticipated embarrassment and trust in robot. In other words, this paper bridges findings about anticipated embarrassment coping behaviours and the effect of robot anxiety. *Eightly* and *lastly*, this research contributes to literature on robot designs as it proves that extremely anthropomorphized designs effectively elicit greater robot anxiety with respect to other kinds of robot designs.

3.3.2 - Managerial contribution

This research also offers some insights that could guide managerial decisions concerning the implementation of an effective strategy for the use of robots in the service encounter. In a context in which companies are looking for solutions to limit the social interactions with employees due to the spread of COVID-19, the use of service robots could become even more relevant because they create social presence without being actual human beings. In order to pave the way for an effective and appropriate use of robots in the service encounter it is crucial to understand customer groups more likely to trust the robot advice, factors that undermine trust in robot advice and robot characteristics that reduce the effects of factors undermining robot trust. And this was exactly the focus of this research.

De facto, this work identifies a customer group that is highly prone to rely on service robot's advice: novice customers. What is more, this behavioural segmentation variable is easily distinguishable through customer profiling with respect to variables identified by previous literature. This means that companies can easily identify what customers are more likely to positively react to service robots. This research shows that developing a strategy focusing on the implementation of service robots for targeting expert consumers may not work as well as a strategy aimed at engaging novice consumers.

Another managerial insight than can be drawn from this research is that service robots highly affect decision-making of consumers and this is extremely relevant in retail contexts in which consumers may feel overwhelmed by the variety of products available as in the beauty products retail context.

In addition to that, this work proves that a seemingly detrimental customer feeling such as anticipated embarrassment in the service encounter can be turned into a strength when the customer is provided with the possibility to avoid social interaction through technology-based self-service in the form of a service robot. Because anticipated embarrassment increases the extent to which consumers are willing to comply with the service robot's advice, this increases the efficacy of the machine and it improves the overall success of the strategy for the implementation of service robots. This means that company using service robots could develop an effective way for both diminishing anticipated discomfort of certain consumers while appropriately supporting them throughout their customer journey.

Another key insight is that companies that decide to implement such strategy should be aware of the level of robot anxiety experienced by target customers because this can seriously harm the efficacy of the strategy. A proxy for estimating that would be considering whether target customers exhibit features that were proved to be negatively correlated with robot anxiety such as education, gender, nationality etc… (Reich & Eyssel, 2013).

Lastly, this research partially confirmed findings concerning the effect of design on robot anxiety and it proves that extremely anthropomorphized designs are to be avoided because they trigger a feeling of uncanniness in consumers, diminishing the extent to which they are willing to trust them.

3.3.3 - Limitations and suggestions for further research

As it was mentioned before, this study was conducted through an online experiment. This was due to practical limitations and the impossibility to collect data in physical lab experiment or, even better, in a real service encounter with real service robots. However, Savela, Turja and Oksanen (2017) proved that conducting in lab or on the field real experiments lead to substantially different results when it comes to robot anxiety. Further research could replicate this experiment in such conditions to verify actual robot anxiety and how it is different from self-reported robot anxiety.

Another limitation of this study concerns the sample selected, indeed, in order to gain significant insights about the beauty industry the sample has been selected to match target customers for make-up products. Thus, because such items are predominantly used by women, the sample of this study was mainly made of women. However, as it was demonstrated by Reich and Eyssel (2013) this group has a tendency to exhibit higher levels of robot anxiety. As a consequence, replicating this experiment in a different industry which targets both men and women may lead to different results. Future research could investigate this matter.

Moreover, this experiment only tested four designs that may have been perceived similar by respondents, future research could test for different designs or even same design kinds but with different robots to test for this effect. For instance, this study did not investigate the role of physical presence on weight on advice because to measure the effect of such a feature the experiment was required to be conducted in a physical lab with physical and non-physical robots. Further studies could address this question. Moreover, van Pinxteren et al. (2019) proved that different kinds of anthropomorphic cues have different effect on people's willingness to trust robots. This is was also proved to be influenced by discomfort caused by the robot such that participants experiencing high discomfort in HRI were demonstrated to prefer robots that behave like human-beings while people experiencing low levels of robot anxiety were proved to prefer robots that look like human beings (van

Pinxteren et al. 2019). Future research could investigate whether discomfort caused by anticipated embarrassment triggers a similar effect.

Lastly, this study did not focus on characteristics such as perceived warmth and competence of robots and the combination of perception of such features and embarrassment. Future research could test that and verify if that is the reason why cute design combined with embarrassment was proved to decrease the level of trust afforded to that specific robot.

REFERENCES

Aggarwal, P., & McGill, A. (2007). Is That Car Smiling at Me? Schema Congruity as a Basis for Evaluating Anthropomorphized Products. *Journal Of Consumer Research*, 34(4), 468-479. doi: 10.1086/518544

Alba, J., & Hutchinson, J. (1987). Dimensions of Consumer Expertise. *Journal Of Consumer Research*, 13(4), 411. doi: 10.1086/209080

Altmann, J., & Sauer, F. (2017). Autonomous Weapon Systems and Strategic Stability. *Survival*, *59*(5), 117-142. doi: 10.1080/00396338.2017.1375263

Askarpour, M., Mandrioli, D., Rossi, M., & Vicentini, F. (2019). Formal model of human erroneous behavior for safety analysis in collaborative robotics. *Robotics And Computer-Integrated Manufacturing*, *57*, 465-476. doi: 10.1016/j.rcim.2019.01.001

Baumeister, R., Bratslavsky, E., Finkenauer, C., & Vohs, K. (2001). Bad is Stronger than Good. *Review Of General Psychology*, 5(4), 323-370. doi: 10.1037/1089-2680.5.4.323

Bettman, J., & Park, C. (1980). Effects of Prior Knowledge and Experience and Phase of the Choice Process on Consumer Decision Processes: A Protocol Analysis. *Journal Of Consumer Research*, 7(3), 234. doi: 10.1086/208812

Broadbent, E. (2017). Interactions With Robots: The Truths We Reveal About Ourselves. *Annual Review Of Psychology*, 68(1), 627-652. doi: 10.1146/annurev-psych-010416-043958

Broadbent, E., Kumar, V., Li, X., Sollers, J., Stafford, R., MacDonald, B., & Wegner, D. (2013). *Robots with Display Screens: A Robot with a More Humanlike Face Display Is Perceived To Have More Mind and a Better Personality*. Plos ONE, 8(8), e72589. doi: 10.1371/journal.pone.0072589

Brosnan, M. (2002). Technophobia: *The Psychological Impact of Information Technology*. London: Routledge.

Brucks, M. (1985). The Effects of Product Class Knowledge on Information Search Behavior. *Journal Of Consumer Research*, 12(1), 1. doi: 10.1086/209031

Buell, R., & Norton, M. (2011). The Labor Illusion: How Operational Transparency Increases Perceived Value. *Management Science*, *57*(9), 1564-1579. doi: 10.1287/mnsc.1110.1376

Carpinella, C., Wyman, A., Perez, M., & Stroessner, S. (2017). The Robotic Social Attributes Scale (RoSAS). *Proceedings Of The 2017 ACM/IEEE International Conference On Human-Robot Interaction*. doi: 10.1145/2909824.3020208

Casey, M., Stewart, D., & Wigginton, C. (2020). Robots on the move: Professional service robots set for double-digit growth. Retrieved 28 March 2020, from https://www2.deloitte.com/global/en/insights/industry/technology/technology-media-and-telecom-predictions/2020/professional-service-robots.html

Caudwell, C., Lacey, C., & Sandoval, E. (2019). The (Ir)relevance of Robot Cuteness. Proceedings Of The 31St Australian Conference On Human-Computer-Interaction. doi: 10.1145/3369457.3369463

Chandler, J., & Schwarz, N. (2010). Use does not wear ragged the fabric of friendship: Thinking of objects as alive makes people less willing to replace them. *Journal of Consumer Psychology*, 20, 138–145. doi: 10.1016/j.jcps.2009.12.008

Chase, W., & Simon, H. (1973). Perception in chess. *Cognitive Psychology*, *4*(1), 55-81. doi: 10.1016/0010-0285(73)90004-2

Dagger, T., & Sweeney, J. (2007). Service Quality Attribute Weights - How Do Novice and Longer-Term Customers Construct Service Quality Perceptions?. *Journal Of Service Research*, 10(1), 22-42. doi: 10.1177/1094670507303010

Dahl, D., Manchanda, R., & Argo, J. (2001). Embarrassment in Consumer Purchase: The Roles of Social Presence and Purchase Familiarity. *Journal Of Consumer Research*, 28(3), 473-481. doi: 10.1086/323734

Dawes, R. (1979). The robust beauty of improper linear models in decision making. *American Psychologist*, *34*(7), 571-582. doi: 10.1037/0003-066x.34.7.571

Dawes, R., Faust, D., & Meehl, P. (1989). Clinical versus actuarial judgment. *Science*, *243*(4899), 1668-1674. doi: 10.1126/science.2648573

de Graaf, M., & Ben Allouch, S. (2013). Exploring influencing variables for the acceptance of social robots. Robotics And Autonomous Systems, 61(12), 1476-1486. doi: 10.1016/j.robot.2013.07.007

Demeure, V., Niewiadomski, R., & Pelachaud, C. (2011). How Is Believability of a Virtual Agent Related to Warmth, Competence, Personification, and Embodiment?. *Presence: Teleoperators And Virtual Environments*, 20(5), 431-448. doi: 10.1162/pres_a_00065

DeNisco Rayome, A. (2018). How Sephora is leveraging AR and AI to transform retail and help customers buy cosmetics. Retrieved 17 April 2020, from https://www.techrepublic.com/article/how-sephora-is-leveraging-ar-and-ai-to-transform-retail-and-help-customers-buy-cosmetics/

Devlin, J. (2011). Evaluative cues and services: the effect of consumer knowledge. *Journal Of Marketing Management*, 27(13-14), 1366-1377. doi: 10.1080/0267257x.2011.624533

Dietvorst, B., Simmons, J., & Massey, C. (2015). Algorithm aversion: People erroneously avoid algorithms after seeing them err. *Journal Of Experimental Psychology*: General, 144(1), 114-126. doi: 10.1037/xge0000033

Epley, N., Waytz, A., & Cacioppo, J. (2007). On seeing human: A three-factor theory of anthropomorphism. *Psychological Review*, 114(4), 864-886. doi: 10.1037/0033-295x.114.4.864

FentyBeauty.com. (2020). Fenty Beauty - PRO FILT'R SOFT MATTE LONGWEAR FOUNDATION. Retrieved 6 May 2020, from https://www.fentybeauty.com/pro-filtr-soft-matte-longwear-foundation/FB30006.html

Fiske, S., Cuddy, A., & Glick, P. (2007). Universal dimensions of social cognition: warmth and competence. *Trends In Cognitive Sciences*, 11(2), 77-83. doi: 10.1016/j.tics.2006.11.005

Fogg, B., & Nass, C. (1997). How users reciprocate to computers. *CHI '97 Extended Abstracts On Human Factors In Computing Systems Looking To The Future* - CHI '97. doi: 10.1145/1120212.1120419

Gilovich, T., & Savitsky, K. (1999). The Spotlight Effect and the Illusion of Transparency. *Current Directions In Psychological Science*, *8*(6), 165-168. doi: 10.1111/1467-8721.00039

Gino, F., & Moore, D. (2006). Effects of task difficulty on use of advice. *Journal Of Behavioral Decision Making*, *20*(1), 21-35. doi: 10.1002/bdm.539

Grace, D. (2007). How Embarrassing! An Exploratory Study of Critical Incidents Including Affective Reactions. *Journal Of Service Research*, 9(3), 271-284. doi: 10.1177/1094670507300905

Gray, H., Gray, K., & Wegner, D. (2007). Dimensions of Mind Perception. *Science*, 315(5812), 619-619. doi: 10.1126/science.1134475

Grewal, D., Noble, S., Roggeveen, A., & Nordfalt, J. (2019). The future of in-store technology. *Journal Of The Academy Of Marketing Science*, *48*(1), 96-113. doi: 10.1007/s11747-019-00697-z

Hanson Robotics. (2020). *Hanson Robotics - Sophia* [Image]. Retrieved from https://www.hansonrobotics.com/sophia/

Hayes, A. (2017). Partial, conditional, and moderated moderated mediation: Quantification, inference, and interpretation. *Communication Monographs*, *85*(1), 4-40. doi: 10.1080/03637751.2017.1352100

Healy, P., & Moore, D. (2007). The Trouble With Overconfidence. *SSRN Electronic Journal*. doi: 10.2139/ssrn.1001821

Hellén, K., & Sääksjärvi, M. (2013). Development of a scale measuring childlike anthropomorphism in products. *Journal Of Marketing Management*, *29*(1-2), 141-157. doi: 10.1080/0267257x.2012.759989

Higuchi, M., & Fukada H. (2002), *"A Comparison of Four Causal Factors of Embarrassment in Public and Private Situations," The Journal of Psychology*, 136 (4), 399-406.

Hinks, T. (2020). Fear of Robots and Life Satisfaction. *International Journal Of Social Robotics*. doi: 10.1007/s12369-020-00640-1

Hoa, T., & Cabibihan, J. (2012). Cute and soft. *Proceedings Of The Workshop At SIGGRAPH Asia On - WASA* '12. doi: 10.1145/2425296.2425310

Hoffman, G., Forlizzi, J., Ayal, S., Steinfeld, A., Antanitis, J., & Hochman, G., Hochendoner, E., & Finkenaur, J. (2015). Robot Presence and Human Honesty. *Proceedings Of The Tenth Annual ACM/IEEE International Conference On Human-Robot Interaction* - HRI '15. doi: 10.1145/2696454.2696487

Honda. (2020). *Honda - Asimo* [Image]. Retrieved from https://asimo.honda.com/

Huang, M., & Rust, R. (2017). Technology-driven service strategy. *Journal Of The Academy Of Marketing Science*, *45*(6), 906-924. doi: 10.1007/s11747-017-0545-6

Ivanov, S. and Webster, C. (2019), Conceptual framework of the use of robots, artificial intelligence and service automation in travel, tourism, and hospitality companies. *Robots, Artificial Intelligence and Service Automation in Travel, Tourism and Hospitality*, ISBN: 978-1-78756-688-0, Emerald Publishing, London.

Ivaldi, S., Lefort, S., Peters, J., Chetouani, M., Provasi, J., & Zibetti, E. (2016). Towards Engagement Models that Consider Individual Factors in HRI: On the Relation of Extroversion and Negative Attitude Towards Robots to Gaze and Speech During a Human–Robot Assembly Task. *International Journal Of Social Robotics*, 9(1), 63-86. doi: 10.1007/s12369-016-0357-8

Kahneman, D. (2011). *Thinking, fast and slow*. New York, NY: Farrar, Straus and Giroux.

Kidd, C., & Breazeal, C. (2008). Robots at home: Understanding long-term human-robot interaction. *2008 IEEE/RSJ International Conference On Intelligent Robots And Systems*. doi: 10.1109/iros.2008.4651113

Kinard, B., Capella, M., & Kinard, J. (2009). The Impact of Social Presence on Technology Based Self-Service Use: The Role of Familiarity. *Services Marketing Quarterly*, 30(3), 303-314. doi: 10.1080/15332960902993593

Knijnenburg, B., Reijmer, N., & Willemsen, M. (2011). Each to his own. *Proceedings Of The Fifth ACM Conference On Recommender Systems* - Recsys '11. doi: 10.1145/2043932.2043960

Krueger, J. (2003). Return of the ego--Self-referent information as a filter for social prediction: Comment on Karniol (2003). *Psychological Review*, *110*(3), 585-590. doi: 10.1037/0033-295x.110.3.585

L'Oréal.com. (2020). L'Oréal Unveils Perso, The World's First AI-Powered Device For Skincare And Cosmetics - L'Oréal Group | World Leader in Beauty | Official Website. Retrieved 17 April 2020, from https://www.loreal.com/media/news/2020/january/perso-ces-innovation

Leroi-Werelds, S. (2019). An update on customer value: state of the art, revised typology, and research agenda. *Journal Of Service Management*, *30*(5), 650-680. doi: 10.1108/josm-03-2019-0074

Lindner, Evelin G. (2001), *"Humiliation and the Human Condition: Mapping a Minefield,"* Human Rights Review, 2 (2), 46-63.

Logg, J., Minson, J., & Moore, D. (2019). Algorithm appreciation: People prefer algorithmic to human judgment. *Organizational Behavior And Human Decision Processes*, 151, 90-103. doi: 10.1016/j.obhdp.2018.12.005

Londono, J., Davies, K., & Elms, J. (2017). Extending the Theory of Planned Behavior to examine the role of anticipated negative emotions on channel intention: The case of an embarrassing product. *Journal Of Retailing And Consumer Services*, 36, 8-20. doi: 10.1016/j.jretconser.2016.12.002

MacDorman, Karl F. (2005), "Mortality Salience and the Uncanny Valley," in Humanoid Robots, *2005 5th IEEE-RAS International Conference*, 399–405.

Mahroof, K. (2019). A human-centric perspective exploring the readiness towards smart warehousing: The case of a large retail distribution warehouse. *International Journal Of Information Management*, *45*, 176-190. doi: 10.1016/j.ijinfomgt.2018.11.008

Mann, J., MacDonald, B., Kuo, I., Li, X., & Broadbent, E. (2015). People respond better to robots than computer tablets delivering healthcare instructions. *Computers In Human Behavior*, 43, 112-117. doi: 10.1016/j.chb.2014.10.029

Mathur, M., & Reichling, D. (2016). Navigating a social world with robot partners: A quantitative cartography of the Uncanny Valley. *Cognition*, 146, 22-32. doi: 10.1016/j.cognition.2015.09.008

Mayfield Robotics. (2020). *https://www.heykuri.com/explore-kuri/* [Image].

Mende, M., Scott, M., van Doorn, J., Grewal, D., & Shanks, I. (2019). Service Robots Rising: How Humanoid Robots Influence Service Experiences and Elicit Compensatory Consumer Responses. *Journal Of Marketing Research*, 56(4), 535-556. doi: 10.1177/0022243718822827

Miller, R. S. (1996). Embarrassment: Poise and peril in everyday life. New York: Guilford Press.

Mittal, V., Kumar, P., & Tsiros, M. (1999). Attribute-Level Performance, Satisfaction, and Behavioral Intentions over Time: A Consumption-System Approach. *Journal Of Marketing*, 63(2), 88-101. doi: 10.1177/002224299906300206

Moon, Y. (2000). Intimate Exchanges: Using Computers to Elicit Self-Disclosure From Consumers. *Journal Of Consumer Research,* 26(4), 323-339. doi: 10.1086/209566

Moore, S., Dahl, D., Gorn, G., & Weinberg, C. (2006). Coping with condom embarrassment. *Psychology, Health & Medicine*, *11*(1), 70-79. doi: 10.1080/13548500500093696

Mori M. (1970). *The uncanny valley*. Energy 7:33–35

Mori, M., MacDorman, K., & Kageki, N. (2012). The Uncanny Valley [From the Field]. *IEEE Robotics & Automation Magazine,* 19(2), 98-100. doi: 10.1109/mra.2012.2192811

Nass, C., & Moon, Y. (2000). Machines and Mindlessness: Social Responses to Computers. *Journal Of Social Issues,* 56(1), 81-103. doi: 10.1111/0022-4537.00153

Nass, C., Moon, Y., & Green, N. (1997). Are Machines Gender Neutral? Gender-Stereotypic Responses to Computers With Voices. *Journal Of Applied Social Psychology,* 27(10), 864-876. doi: 10.1111/j.1559-1816.1997.tb00275.x

Nelson, P. (1970). Information and Consumer Behavior. *Journal Of Political Economy*, *78*(2), 311-329. doi: 10.1086/259630

Nenkov, G., & Scott, M. (2014). "So Cute I Could Eat It Up": Priming Effects of Cute Products on Indulgent Consumption. *Journal Of Consumer Research*, 41(2), 326-341. doi: 10.1086/676581

Niewiadomski, R., Demeure, V., & Pelachaud, C. (2010). Warmth, Competence, Believability and Virtual Agents. Intelligent Virtual Agents, 272-285. doi: 10.1007/978-3-642-15892-6_29

Nomura, T., Suzuki, T., Kanda, T., & Kato, K. (2006). Measurement of Anxiety toward Robots. ROMAN 2006 - *The 15Th IEEE International Symposium On Robot And Human Interactive Communication.* doi: 10.1109/roman.2006.314462

P&G.com. (2019). Retrieved 20 April 2020, from https://news.pg.com/sites/pg.newshq.businesswire.com/files/fact_sheet/file/Opte_Fact_Sheet.pdf

Park, C., & Lessig, V. (1981). Familiarity and Its Impact on Consumer Decision Biases and Heuristics. *Journal Of Consumer Research*, 8(2), 223. doi: 10.1086/208859

Rao, A., & Monroe, K. (1988). The Moderating Effect of Prior Knowledge on Cue Utilization in Product Evaluations. *Journal Of Consumer Research*, 15(2), 253. doi: 10.1086/209162

Reich, N., & Eyssel, F. (2013). Attitudes towards service robots in domestic environments: The role of personality characteristics, individual interests, and demographic variables. Paladyn, *Journal Of Behavioral Robotics*, 4(2). doi: 10.2478/pjbr-2013-0014

Sabelli, A., & Kanda, T. (2015). Robovie as a Mascot: A Qualitative Study for Long-Term Presence of Robots in a Shopping Mall. *International Journal Of Social Robotics*, 8(2), 211-221. doi: 10.1007/s12369-015-0332-9

Savela, N., Turja, T., & Oksanen, A. (2017). Social Acceptance of Robots in Different Occupational Fields: A Systematic Literature Review. *International Journal Of Social Robotics*, *10*(4), 493-502. doi: 10.1007/s12369-017-0452-5

Siegel, M., Breazeal, C., & Norton, M. (2009). Persuasive Robotics: The influence of robot gender on human behavior. *2009 IEEE/RSJ International Conference On Intelligent Robots And Systems*. doi: 10.1109/iros.2009.5354116

Smith, D., & Park, C. (1992). The Effects of Brand Extensions on Market Share and Advertising Efficiency. *Journal Of Marketing Research*, *29*(3), 296. doi: 10.2307/3172741

SoftBank Robotics. (2020). *SoftBank Robotics - Pepper* [Image]. Retrieved from https://softbankrobotics.com/us/pepper

Sprengelmeyer, R., Perrett, D., Fagan, E., Cornwell, R., Lobmaier, J., & Sprengelmeyer, A. et al. (2009). The Cutest Little Baby Face. *Psychological Science*, 20(2), 149-154. doi: 10.1111/j.1467-9280.2009.02272.

Stanovich, K., & West, R. (2000). Individual differences in reasoning: Implications for the rationality debate?. *Behavioral And Brain Sciences*, 23(5), 645-665. doi: 10.1017/s0140525x00003435

Statista. (2019). Robotics - A Statista dossier on the global robotics market and application areas. Retrieved 17 April 2020, from https://www.statista.com/study/64326/robotics/

Thomas, D. (2019). Five tech trends shaping the beauty industry. Retrieved 17 April 2020, from https://www.bbc.com/news/business-48369970

Tversky, A., & Kahneman, D. (1974). Judgment under Uncertainty: Heuristics and Biases. *Science*, 185(4157), 1124-1131. doi: 10.1126/science.185.4157.1124

UBTECH Robotics. (2020). *UBTECH Robotics - Cruzr* [Image]. Retrieved from https://www.ubtrobot.com/products/cruzr

Uzzi, B. (2019). How Olay's AI-Powered Consultation Disrupts The Cosmetics Industry. Retrieved 17 April 2020, from https://www.forbes.com/sites/brianuzzi/2019/05/01/how-olays-ai-powered-consultation-disrupts-the-cosmetics-industry/#1fb2bda93e06

van Pinxteren, M., Wetzels, R., Rüger, J., Pluymaekers, M., & Wetzels, M. (2019). Trust in humanoid robots: implications for services marketing. *Journal Of Services Marketing*, 33(4), 507-518. doi: 10.1108/jsm-01-2018-0045

Wainer, J., Feil-seifer, D., Shell, D., & Mataric, M. (2006). The role of physical embodiment in human-robot interaction. ROMAN 2006 - *The 15Th IEEE International Symposium On Robot And Human Interactive Communication*. doi: 10.1109/roman.2006.314404

Walkington, C., & Bernacki, M. (2018). Personalizing Algebra to Students' Individual Interests in an Intelligent Tutoring System: Moderators of Impact. *International Journal Of Artificial Intelligence In Education*, *29*(1), 58-88. doi: 10.1007/s40593-018-0168-1

Waytz, A., & Norton, M. (2014). Botsourcing and outsourcing: Robot, British, Chinese, and German workers are for thinking—not feeling—jobs. *Emotion*, 14(2), 434-444. doi: 10.1037/a0036054

Waytz, A., Heafner, J., & Epley, N. (2014). The mind in the machine: Anthropomorphism increases trust in an autonomous vehicle. *Journal Of Experimental Social Psychology*, 52, 113-117. doi: 10.1016/j.jesp.2014.01.005

Wirtz, J., Patterson, P., Kunz, W., Gruber, T., Lu, V., Paluch, S., & Martins, A. (2018). Brave new world: service robots in the frontline. *Journal Of Service Management*, 29(5), 907-931. doi: 10.1108/josm-04-2018-0119

Xiong, Y., Peng, C., Grimstad, L., From, P., & Isler, V. (2019). Development and field evaluation of a strawberry harvesting robot with a cable-driven gripper. *Computers And Electronics In Agriculture*, *157*, 392-402. doi: 10.1016/j.compag.2019.01.009

Yaniv, I., & Kleinberger, E. (2000). Advice Taking in Decision Making: Egocentric Discounting and Reputation Formation. *Organizational Behavior And Human Decision Processes*, *83*(2), 260-281. doi: 10.1006/obhd.2000.2909

Yeomans, M., Shah, A., Mullainathan, S., & Kleinberg, J. (2019). Making sense of recommendations. *Journal Of Behavioral Decision Making*, *32*(4), 403-414. doi: 10.1002/bdm.2118

APPENDIX A - Analysis of the service robot market

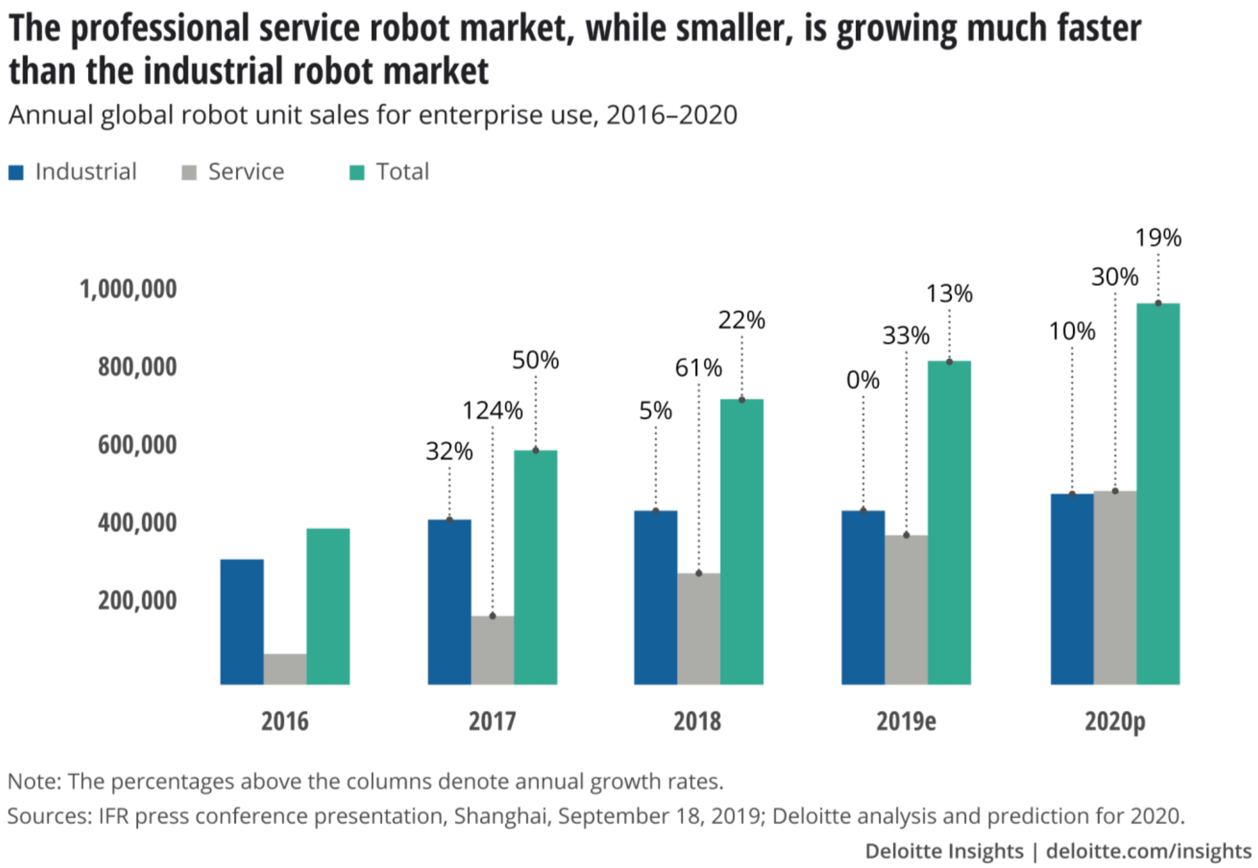


Figure 1 Annual global robot unit sales for enterprise use, 2016-2020. Casey, Stewart & Wigginton (2020)

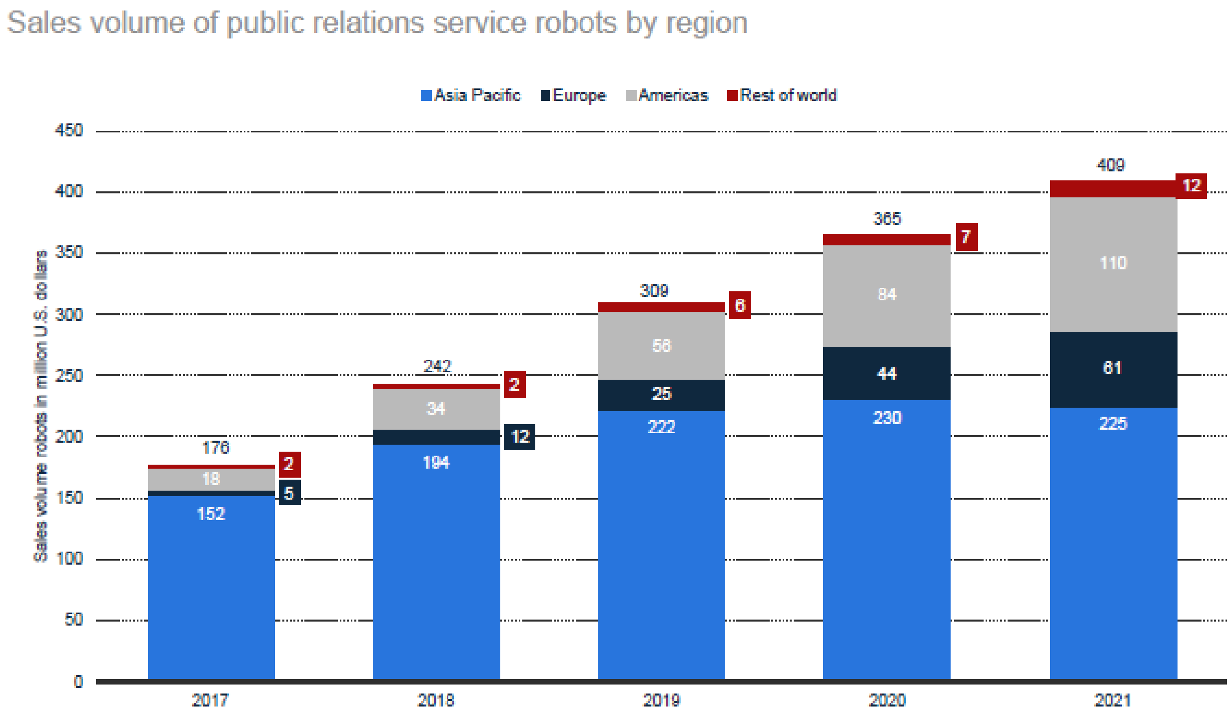


Figure 2. Sales volume of public relations service robots by region. Statista, (2019)

APPENDIX B – Robot designs

Figure 1. Cruzr (control condition): not anthropomorphized, not cute. (UBTECH Robotics, 2020)

Cruzr's video shown in the experiment: https://urly.it/366zw

Figure 2. Asimo (moderately anthropomorphized condition): anthropomorphized, not cute. (Honda, 2020)

Asimo's video shown in the experiment: https://urly.it/366zj

Figure 3. Kuri (cute condition): not anthropomorphized, cute (Mayfield Robotics, 2020)

Kuri's video shown in the experiment: https://urly.it/366z_

Figure 4. Sophia (extremely anthropomorphized condition) : anthropomorphized, not cute. (Hanson Robotics, 2020)

Sophia's video shown in the experiment: https://urly.it/366-3

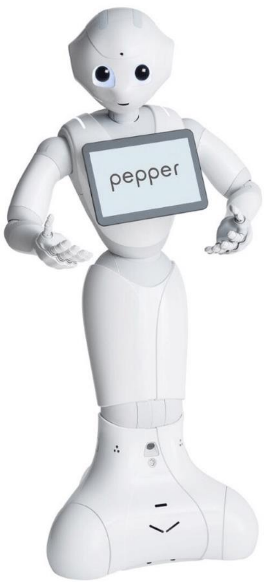


Figure 5. Pepper (anthropomorphized and cute condition) : anthropomorphized, cute (SoftBank Robotics, 2020)

Pepper's video shown in the experiment: https://urly.it/366za

APPENDIX C – Foundation shades

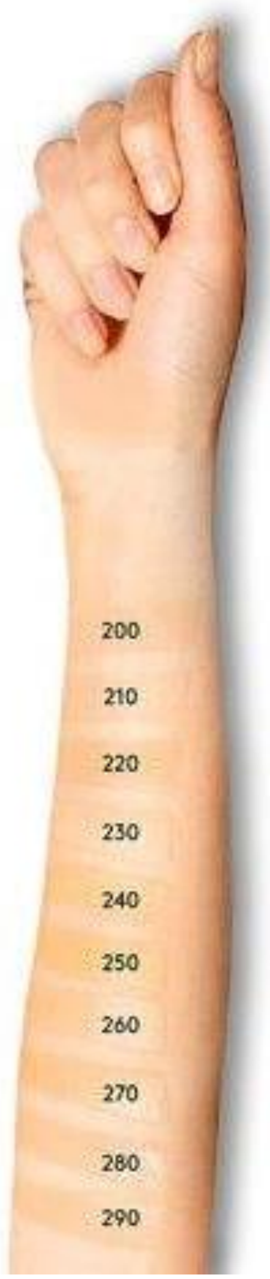


Figure 1 Fondation shades – First choice and final choice

(FentyBeauty.com, 2020)

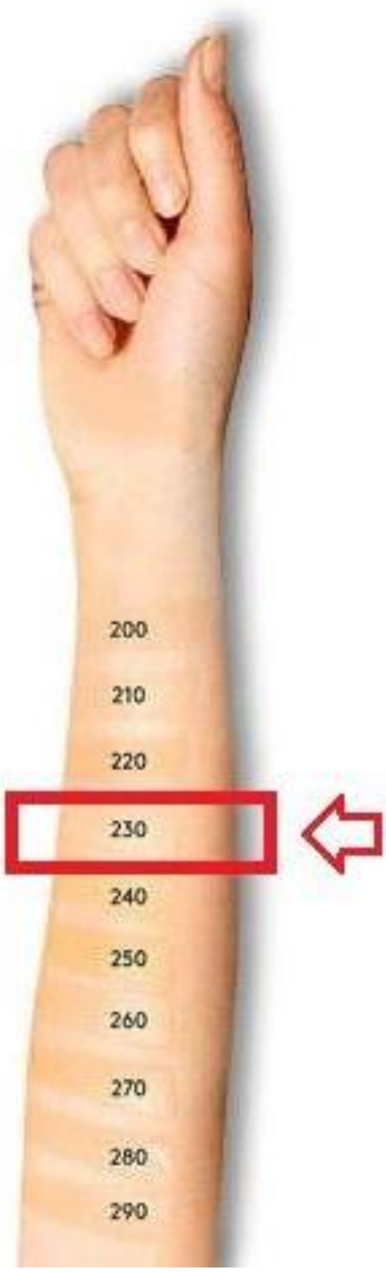


Figure 2 Fondation shades – Robot advice

(FentyBeauty.com, 2020)

APPENDIX D – Variables distribution

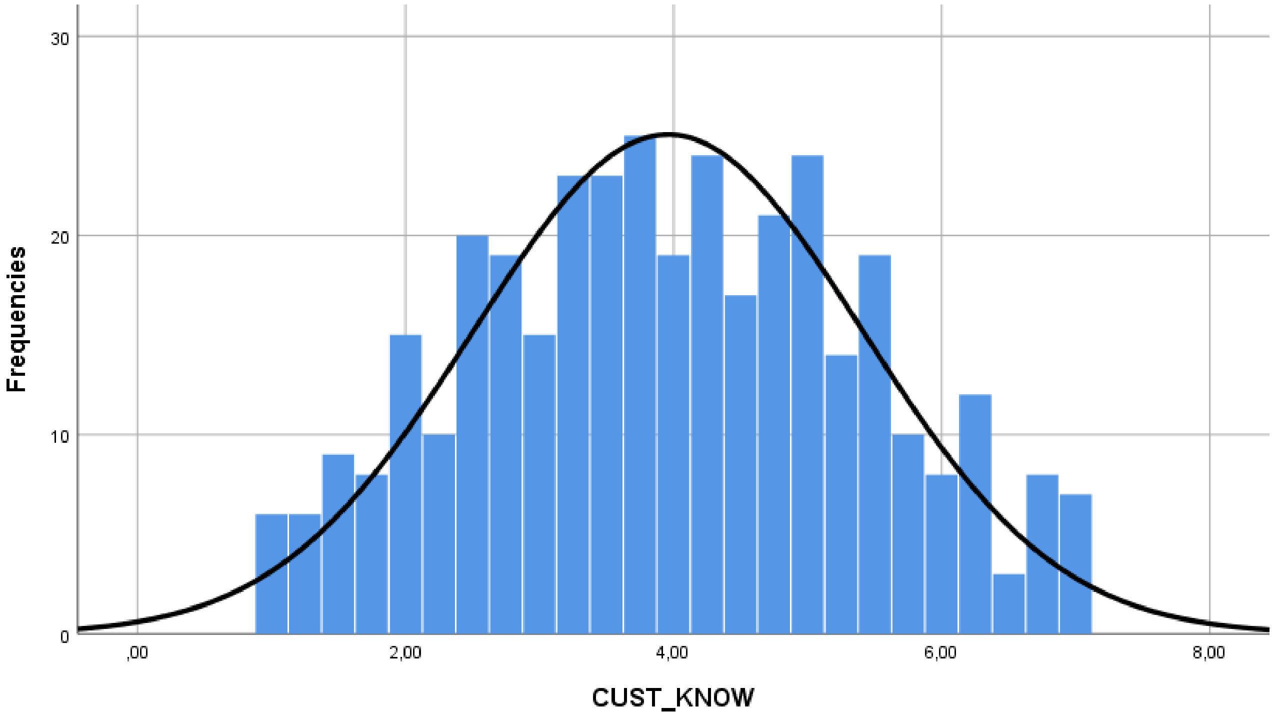


Figure 1 – Customer knowledge distribution

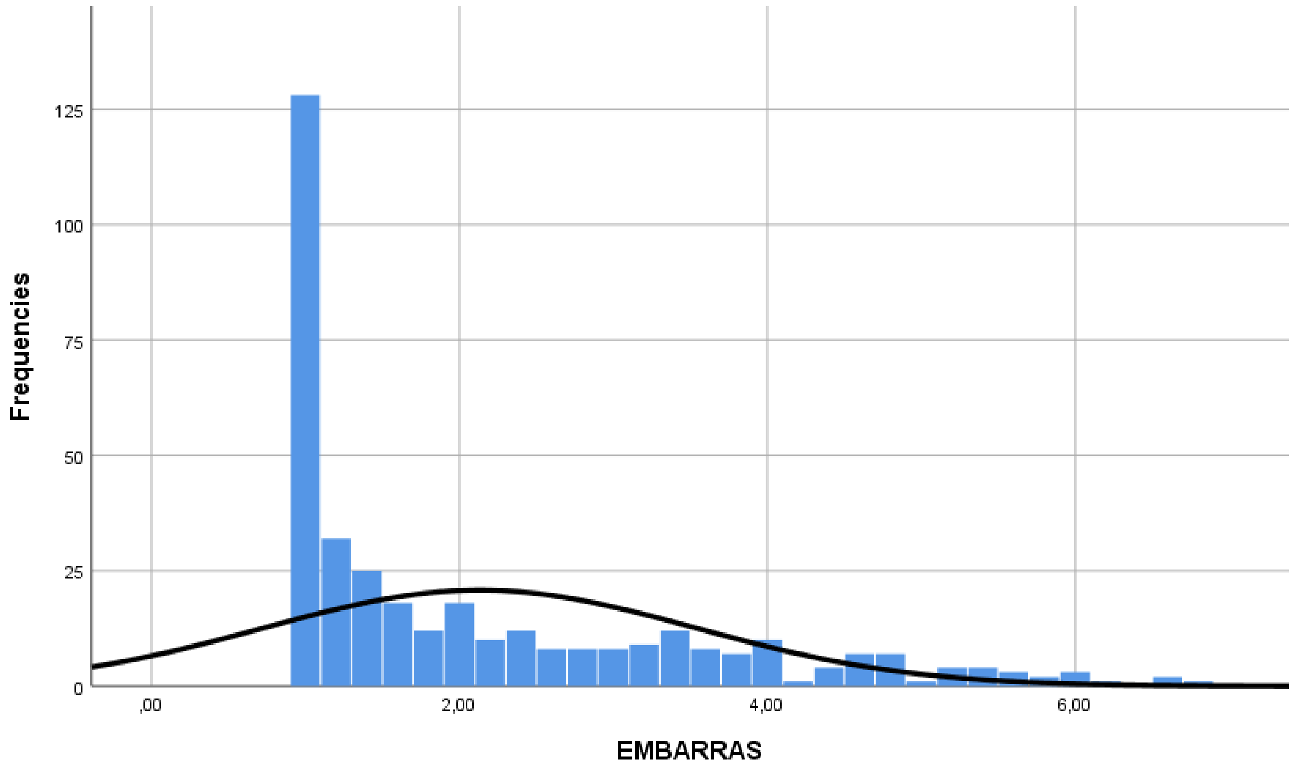


Figure 2 - Embarrassment distribution

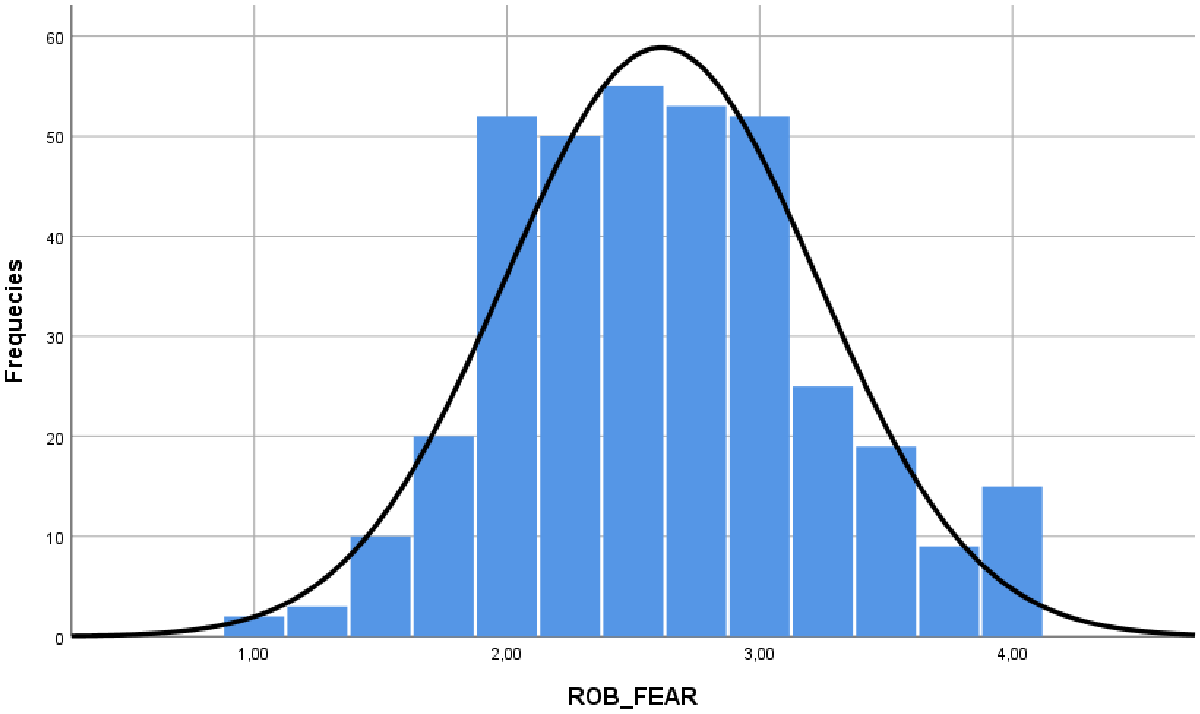


Figure 3 – Robot anxiety distribution

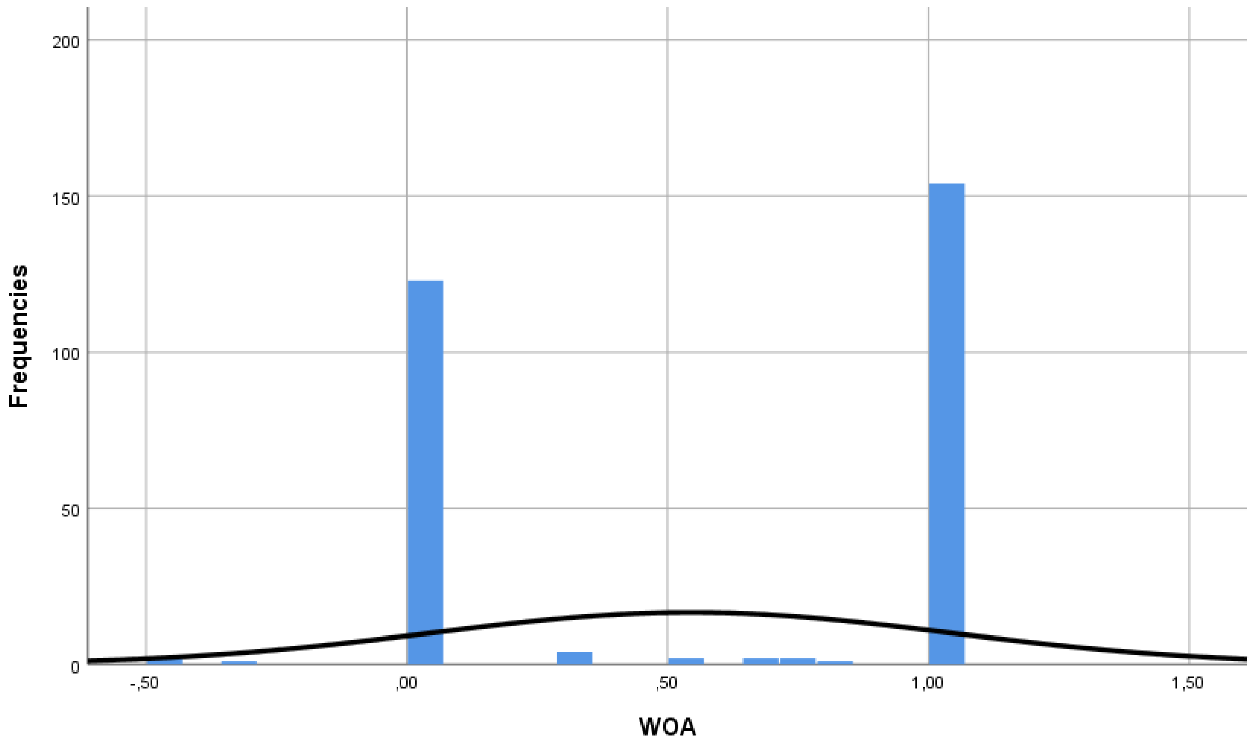


Figure 4 – WOA distribution

APPENDIX E – Descriptive statistics of the sample

Gender		
	Frequency	Percentage
Male	3	0.8
Female	362	99.2
Total	365	100.0

Table 1 – Gender frequency statistics

Job		
	Frequency	Percentage
Employed in the beauty industry	13	3.6
Employed in other industries	75	20.5
Student	261	71.5
Retired	2	0.5
Unemployed	14	3.8
Total	365	100.0

Table 2 – Job frequency statistics

Education		
	Frequency	Percentage
High school	138	37.8
Bachelor	157	43.0
Master	69	18.9
PhD	1	0.3
Total	365	100.0

Table 3 – Education frequency statistics

Foundation usage		
	Frequency	Percentage
Everyday	115	31.5
2-3 times per week	82	22.5
Once per week	41	11.2
Once per month	54	14.8
Never	73	20.0
Total	365	100.0

Table 4 – Foundation usage frequency statistics

Age					
	N	Min.	Max.	Mean	SD
Age	365	17.00	65.00	25.7233	8.83192

Table 5 – Age descriptive statistics

APPENDIX F – Bootstrap results

OUTCOME VARIABLE : EMBARRASS					
	Coeff	BootMean	BootSE	BootLLCI	BootULCI
constant	0.0011	0.0011	0.0555	-0.1058	0.113
CUST_KNOW	-0.2654	-0.2649	0.0582	-0.3767	-0.1499
OUTCOME VARIABLE : WOA					
	Coeff	BootMean	BootSE	BootLLCI	BootULCI
constant	0.4834	0.4814	0.058	0.3685	0.5964
CUST_KNOW	-0.0684	-0.0675	0.03	-0.1259	-0.0095
EMBARRAS	0.105	0.104	0.0474	0.0081	0.1944
ROB_FEAR	-0.1238	-0.1278	0.0664	-0.257	0.0026
Int_1	-0.0922	-0.0949	0.0514	-0.2003	-0.0008
Asimo	0.0404	0.0412	0.0828	-0.1202	0.2037
Kuri	0.0345	0.0324	0.0803	-0.1262	0.1886
Sophia	0.1253	0.1303	0.082	-0.0322	0.2858
Int_2	-0.0564	-0.0514	0.0852	-0.2154	0.1186
Int_3	-0.2006	-0.2082	0.0738	-0.3575	-0.0685
Int_4	0.0249	0.0367	0.0742	-0.1095	0.1831
Int_5	-0.0581	-0.0618	0.0929	-0.2448	0.1223
Int_6	0.0017	0.0076	0.0867	-0.1586	0.1784
Int_7	0.0091	0.0065	0.0844	-0.1582	0.1739
Int_8	0.0744	0.0679	0.1006	-0.1349	0.2594
Int_9	0.0193	0.0228	0.0731	-0.1135	0.1756
Int_10	0.0782	0.0665	0.0768	-0.0903	0.2118
Product terms key:					
Int_1 :	EMBARRAS	x	ROB_FEAR		
Int_2 :	EMBARRAS	x	Asimo		
Int_3 :	EMBARRAS	x	Kuri		
Int_4 :	EMBARRAS	x	Sophia		
Int_5 :	ROB_FEAR	x	Asimo		
Int_6 :	ROB_FEAR	x	Kuri		
Int_7 :	ROB_FEAR	x	Sophia		
Int_8 :	EMBARRAS	x	ROB_FEAR x		Asimo
Int_9 :	EMBARRAS	x	ROB_FEAR x		Kuri
Int_10 :	EMBARRAS	x	ROB_FEAR x		Sophia

Table 1 – Bootstrap results

Acknowledgements

This project represents the end of a beautiful journey and I believe it is worth spending few words to thank the beautiful people that contributed to it.

I want to thank my thesis supervisor Prof. Giacomo Sillari and my thesis co-supervisor Prof. Giovanni Ponti for helping me throughout the long process of thesis development. Thank you for the insights and support you gave me.

I also want to thank my family for supporting me and encouraging me from the beginning. They taught me to dream big, aim high and to continuously seek for new ways to build a better version of myself.

I want to say thank you to Benedetta, we have been in this together from the very first day, sharing successes and hard times. I wish we could work to our theses side by side as we did for our bachelor, but I am also aware of the fact that you are always with me in everything I do. You are a blessing, do not ever forget that.

I want to thank Gloria, your joy and energy are always an inspiration for me. Thank you for the beautiful human being you are and for always being there for me. Thank you for showing me that anything can be achieved through motivation and determination.

To Joann, for being such an angel. You are sweet, kind and thoughtful, plus you literally spammed my experiment to everyone you know. I love you so much! Thank you so much for being such a great friend.

Thanks to Edo, partner in crime during the mad and desperate study of so many exams. I will miss the carpool to university singing, probably I should say screaming, to Ultimo every day.

Finally, I want to thank my boyfriend Nicholas for the relentless support he gave me from the very beginning of this project. Thank you for the patience, encouragement and inspiration. Thank you for believing in me when I fail to do so and thank you for reminding me that I should do it too. We both know that without you this work would be a lot different. Thank you

LUISS

Dipartimento

di Impresa e Management

Cattedra Specifica: Behavioural economics and consumption theories

Building trust in robots: the interplay of customer knowledge, embarrassment, robot anxiety and robot design on trust in service robots

Prof. Giacomo Sillari

RELATORE

Prof. Giovanni Ponti

CORRELATORE

Matr. 704871

CANDIDATO

Anno Accademico 2019/2020

INDEX

Great technological advances in the field of robotics are allowing for the implementation of autonomous robots able to carry out extremely complex tasks which increases the extent to which they can cater customers in the service context (Wirtz et al., 2018). Service robots entail several benefits, both for companies such as cost reductions, enhanced efficiency and effectiveness, and for consumers such as convenience and availability (van Pinxteren et al. 2019). Moreover, as it is the case for Technology-Based Self-Service (TBSS), they provide the possibility to avoid social interactions with human service providers, which is extremely valuable in situations in which consumers may anticipate or perceive embarrassment due to service encounters with human agents (Londono, Davies & Elms, 2017). However, several factors hinder the acceptance of service robots, as well as the extent to which individuals are willing to trust them (Broadbent, 2017). It is then crucial to identify what particular characteristics of customers and of service robots can facilitate or hinder trust in service robots which was proved to be crucial for service robot acceptance (Wirtz et al., 2018). Specifically, this study investigates the interplay of customer knowledge of the product or service, anticipated embarrassment in the service encounter, fear of the robot (also termed robot anxiety) and robot design.

To put it simply: if you look at it from the consumer perspective, the way these variables are connected becomes more intuitive. When thinking about your experience as a consumer there are surely certain fields and product domains about which you consider your knowledge above average and others in which you believe it to be below average.

For instance, if you are passionate about make-up, you might have a deep knowledge of what are the characteristics more relevant in the choice of a lipstick or foundation, you are familiar with the most popular brands, you keep up with trends in the industry, you are probably even knowledgeable about complex matters such as chemical formulations of make-up products. You consider yourself to be an expert in this domain. When you want to buy a new foundation you know how the service encounter will unfold, you have been to the store a million times, you know the jargon so if you need further information you are confident in your ability to ask the right questions and understand the answers. The idea of asking for help does not make you uncomfortable because you do not think that it would put you in an embarrassing situation. You probably do not even need help in the process because you can make the decision on your own.

On the other hand, if you are not so keen about make-up you are probably unsure about what you should look for, you feel overwhelmed by the huge variety of different shades available, you are probably only familiar with a few brands, chemical formulations are completely obscure to you and you are not familiar with the make-up jargon. This means that you are not sure that you can even ask the right questions, let alone understand the answers. You are probably not very confident in your ability to make the right choice on your own and the idea of asking for advice makes you uncomfortable. This is because you fear that most people know more about make-up than you do. You would gladly appreciate a piece of advice to guide your decision, but you do not want to feel judged.

This is exactly where service robots could become beneficial. If once in the store you realized that you could ask for assistance to a service robot, your reaction would depend on your level of expertise in make-up. If you are an expert, you would probably believe that you do not need help with your decision, there is no way that an algorithm can pick a better match than you. On the other hand, if you are not an expert you would probably give it a try because that would allow you to avoid the potentially embarrassing interaction.

Clearly, everything this only holds if you have a positive attitude towards the robot advisor. If you are afraid of it, you probably do not trust it and you want to avoid it. The way the robot looks would play a huge role in determining whether you should fear it or not. For instance, if the robot somehow resembles a human being, maybe it has a face and it can smile at you, you would not find it very scary, and the same thing would happen if you found the robot cute. However, if the robot looked too much like a human being you would probably find it creepy and it would scare you.

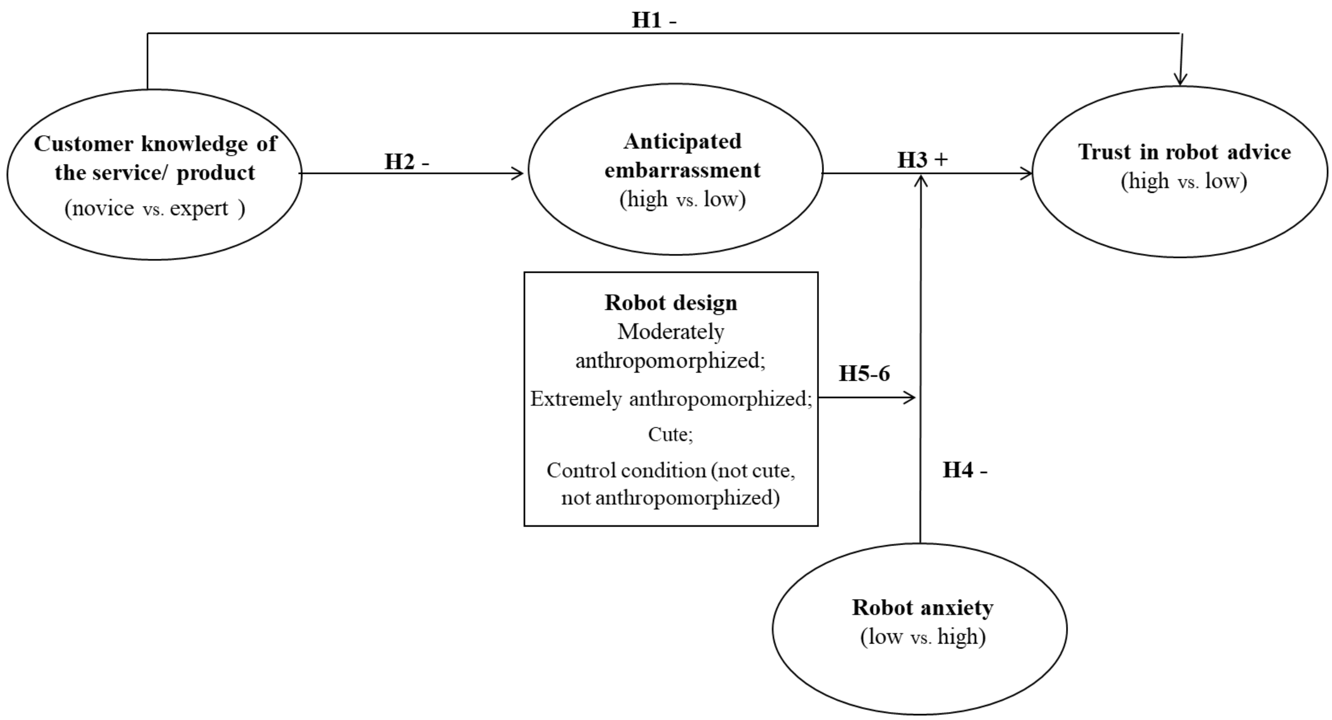
From a retailer perspective, using service robots can be a very effective strategy to support customers' decision making. Understanding what factors are crucial in shaping whether robot advice will be complied with or not is essential for succeeding in the implementation of this plan of action. Using service robots may mean providing a large subset of potential customers with more effective advice, thereby increasing chances of a purchase decision, and using service robots in a way that maximizes customer trust in their recommendation may make the difference between a satisfied, returning customer and one who will not be back. This work provides some insights for the use of customer knowledge of products and services as a practical segmentation variable. Furthermore, it shows that using it too crudely, neglecting the role of anticipated embarrassment, robot anxiety and robot design, would make it less effective as a segmentation variable.

The importance of developing a deeper understanding of these effects is crucial because service robot's acceptance has been demonstrated to be significantly enhanced through exposure to service robots as well as social influence -i.e. the extent to which the technology is perceived to be accepted by the individual's reference group- (de Graaf & Ben Allouch, 2013). Consequently, it is vital for companies to identify customer segments more prone to interact with and trust service robots to boost social influence and pave the way for service robot acceptance and, as a consequence, for extensive use of service robots in customer care.

This study analyses whether customer knowledge can be used as an effective behavioural segmentation variable for the identification of a more effective and appropriate use of service robots for specific customer segments. The first hypothesis of this model is that customers with little knowledge of the product or service are more likely to rely on robot advice. Furthermore, this research proposes that this effect is mediated by anticipated embarrassment. The logic behind this reasoning is based on the fact that lack of product and service knowledge have been demonstrated to be an important antecedent of anticipated embarrassment (Miller, 1996). Moreover, Grace (2007) proved that a common coping behaviour triggered by anticipated embarrassment is avoidance of social interactions in order to preserve their self-image. In such instances, Londono, Davies and Elms (2017) have shown that customers are more willing to rely on technology-based self-service because this allows them to receive the product or service without the intervention of a service employee and this allows them to avoid potentially embarrassing interactions. As a consequence, customer knowledge is expected to negatively influence anticipated embarrassment (hypothesis 2) and trust in robot advice (hypothesis 1). On the other hand, anticipated embarrassment in the service encounter is expected to positively affect trust in robot and reliance to its advice (hypothesis 3).

Moreover, this research investigates the effect of robot anxiety on reliance on robot advice and it analyses what kind of designs are better suited for moderating robot anxiety and increasing robot trust. The application of this kind of technology has been hindered by robot anxiety which decreases service robot acceptance (Nomura et al. 2006; de Graaf & Allouch, 2013; Mende et al. 2019; Mori, 1970; Mori, MacDorman, & Kageki, 2012; Mathur & Reichling, 2016). De Graaf and Allouch (2013) proved that robot anxiety and fear of the robot provoke a sense of discomfort that leads to avoidance of the robot. Thus, the fourth hypothesis of this research predicts that when people are afraid of the robot, they are less likely to trust it and rely on its advice because robot anxiety decreases the positive effect of embarrassment on trust in robot.

However, selecting the right kind of design could help increasing trust in robot advice. In fact, Broadbent (2017) has identified robot design as one of the most important elements affecting robot anxiety. In this regard, prior studies concerning the *uncanny valley effect* (Mori, 1970; Mori, MacDorman, & Kageki, 2012; Mathur & Reichling, 2016) demonstrated people have a tendency to prefer robots with anthropomorphized designs with respect to robots with non-anthropomorphized designs. However, when the robot looks almost perfectly like a human being, people experience a sense of uncanniness towards the robot (Mori, 1970; Mori, MacDorman, & Kageki, 2012; Mathur & Reichling, 2016). Mathur and Reichling (2016) proved that the uncanny valley effect influences trust afforded to the robot. As a consequence, this research predicts that people exposed to robots with moderately anthropomorphised designs experience lower levels of robot anxiety (Hypothesis 5a) while people exposed to robots with extremely anthropomorphized designs experience higher levels of robot anxiety (Hypothesis 5b). Another kind of design tested in this study is the cute one. Indeed, according to Nenkov and Scott (2014) and Caudwell, Lacey and Sandoval (2019) this kind of design usually creates associations to naïve creatures, and it decreases perceive treat stemming from the robot. These characteristics are expected to increase trust afforded to cute robots. Thus, this research predicts that people exposed to robots with cute designs experience lower levels of robot anxiety (hypothesis 6). Graphically the model of this study can pe portrayed as follows:



The structure of this study is as follows. The first chapter presents the model of the study and it provides an introduction about the service robots industry and state of the art in the section 1.1. This section provides evidence concerning the potential of this industry which is expected to dramatically grow in the coming years due to technological changes that are expected to substantially improve performance of service robots. Moreover, section 1.2 introduces the beauty industry which is the field of application of the model, and it shows why service robots represent a potential fit for this industry. De facto, this industry has witnessed a substantial increase in terms of products available for consumers which have been proved to create confusion in non-expert customers (Uzzi, 2019). To address this problem, the biggest brands in the industry have started to include AI-powered recommendation systems to support customers throughout their customer journey (Uzzi, 2019). However, these technologies are not likely to thoroughly engage the customer (Grewal et al. 2019). In addition to that, *algorithm aversion theory* predicts that these kinds of recommendations are sub-optimally integrated by individuals (Dietvorst, Simmons, & Massey, 2015). This suggests that this particular industry is ready to implement service robots in customer care and this could be a solution to address the limitations of currently used technologies.

The second chapter of this research provides a literature review of the main themes touched upon on this introduction. Section 2.1 is dedicated to customer knowledge and it illustrates the reasons why customer journeys of consumers with different levels of expertise in the product or service are different. In particular, the section shows how different levels of customer expertise produce a different set of cognitive tools available for decision making which leads to differences in decision-making processes, outcomes, mental shortcuts, confidence in the decision, preferences for recommendation systems and more.

Section 2.2 presents prior literature's findings about embarrassment and anticipated embarrassment. The section defines the construct as distinct from related concepts such as shame and humiliation. The sub-chapter shows that lack of customer knowledge can generate anticipated embarrassment (Miller,1996) because it is likely to trigger the mental processes discussed in both *social evaluation theory* (Miller, 1996) and *dramaturgic theory* (Higuchi & Fukada, 2002) which construe two important antecedents of embarrassment and anticipated embarrassment. In addition to that, the section highlights two important concepts which predicts that embarrassment has a great impact on consumer behaviour: *emotional loss aversion* (Baumeister et al. 2001) and the *spotlight effect* (Gilovich & Savitsky, 1999). The last part of the embarrassment section discusses related coping behaviours investigated by Grace (2007) and how technology-based self-service has been proved to be beneficial in this context for the purchase of embarrassing products, suggesting that service robots could be beneficial for addressing potentially detrimental embarrassment coping behaviours (Londono, Davies & Elms, 2017).

Section 2.3 introduces and defines robot anxiety (Nomura et al. 2006). It discusses its consequences (Mende et al. 2019) and it analyses its antecedents. Among these there are the *uncanny valley effect* (Mori, 1970; Mori, MacDorman, & Kageki, 2012; Mathur & Reichling, 2016), category confusion (Broadbent, 2017), concerns for job loss threats (Waytz & Norton, 2014), concern for threats to human identity (Mende et al. 2019), and negative associations to diseased or dead bodies (Broadbent, 2017; MacDorman, 2005).

Section 2.4 describes the importance of robot design in shaping individuals' attitudes towards robots and it is divided into 3 sub-sections based on three important design characteristics that have been proved to be crucial in this context: physical embodiement (sub-section 2.4.1), anthropomorphism (sub-section 2.4.2) and cuteness (sub-section 2.4.3).

The last section of chapter two is dedicated to trust in robot advice (section 2.5). The section begins with an explanation of the processes that lead to discount others' advice such as *egocentric discounting (*Yaniv & Kleinberger, 2000), *anchoring and insufficient adjusting* (Tversky & Kahneman, 1974), *egocentric bias* (Krueger, 2003) and *negativity bias* in advisor's reputation formation (Yaniv & Kleinberger, 2000). The section furthermore shows that distrust in advice can be extremely detrimental to accuracy of decision making and that this effect is further amplified when the source of the advice is an algorithm as opposed to a human (Yeomans et al. 2019; Dietvorst, Simmons, & Massey, 2015). However, Gino and Moore (2006) demonstrated that when the task is perceived as difficult, people are less confident in their ability to perform the task independently and tend to seek for advice. This finding suggests that novices, who are more likely to perceive service-related tasks as difficult because of their lack of service expertise, may be more likely to rely on advice. Lastly, the section discusses the importance of robot trust for service robot acceptance and it investigates prior literature's findings about the effect of robot design on robot trust.

The last chapter of this research contains the model, the procedure, the results and the discussion of the experiment of the study. Indeed, section 3.1 describes the model and provides a detailed description of the hypothesis as well as the reasonings behind them.

Section 3.2 discusses the methodology for testing the model. Section 3.2.1 describes the procedure of the pre-test that has been conducted through an online survey with 130 participants to make sure that the robot designs that were to be used in the main study were perceived as expected based on criteria provided by prior literature. Five robot designs have been tested, to do so five comparable videos of five robots have been edited to show the very same actions performed by each robot, even the music in the background has been homologated to avoid biasing perceptions of the designs. A robot named Cruzr was expected to be perceived as neither anthropomorphised nor cute so that it could have been used as control condition in the main study. A robot named *Asimo* was expected to be perceived as moderately anthropomorphized but not cute, so that it could have been used as the moderately anthropomorphised condition in the main study. A robot named *Kuri* was expected to be perceived as not anthropomorphized but cute, so that it could have been used as the cute condition in the main study. A robot named *Sophia* was expected to be perceived as extremely anthropomorphized but not cute, so that it could have been used as the extremely anthropomorphised condition in the main study. And finally, a robot named *Pepper* was expected to be perceived as both anthropomorphized and cute, so that it could have been used as the anthropomorphised and cute condition in the main study. The section also describes the way the online survey has been conducted including videos and questions that participants have been exposed to.

Section 3.2.2 describes findings from the one-way ANOVA and post-hoc analyses conducted on SPSS of the pre-test data. The first four designs have been confirmed to be perceived exactly how it had been anticipated. However, the last one, Pepper, that was expected to be perceived as both cute and anthropomorphized, did not exhibit significant differences in terms of perceptions of these dimensions with respect to the control condition. For this reason, it has been excluded from the analysis of the main study.

Section 3.2.3 describes the procedure of the main study that has been conducted through an online experiment with 374 participants to test the hypotheses of the model. The section also describes the way the online experiment has been conducted including the videos, photos, questions, and the decision task that participants have been exposed to. In practice, participants have been asked to rate their knowledge in the domain of make-up, in particular, the study assessed their expertise with foundation. After that, they have been asked to rate the extent to which they would have felt embarrassed in a situation in which they consulted a shop assistant for buying the right shade of foundation for their skin tone. After that, they have been shown a photo of an arm with various shades of foundation on and they have been asked to choose the shade that they thought they would have bought if they had to decide on their own. The experiment continued randomly showing each participant one video of a robot design selected through the pre-test. After that, participants have been told to imagine that the robot had scanned their skin tone and advised them to select one particular shade. Moreover, participants have been tested for the robot anxiety generated by the particular condition they have been assigned to. After that, they have been asked to make their final decision, fill in an attention check question to make sure they remembered the advice provided, and they have been asked to provide some demographics.

Section 3.2.4 provides the findings of the analysis conducted on SPSS with PROCESS v3.4 model 18 to test the hypothesis of the model which is a second stage conditional moderated mediation (Hayes, 2017). The first four hypothesis have been confirmed demonstrating both the mediating role of anticipated embarrassment in the relation between customer knowledge and trust in robot advice, and the moderating role of robot anxiety on this effect. However, the hypotheses concerning the effect of design on robot anxiety have only partially been confirmed as hypothesis 5b has been proved to be significant suggesting that extremely anthropomorphized designs significantly lead to lower levels of robot anxiety. On the other hand, although moderated anthropomorphized designs and cute design triggered lower levels of robot anxiety in participants, these differences were not proved to be significant.

The last section of the research, section 3.3 includes the discussion concerning the findings of the study including the theoretical contribution (section 3.3.1), managerial contribution (3.3.2) and limitations and suggestions for further research (section 3.3.3).

Results of the experiment conducted confirm the negative significant effect of customer knowledge on weight on advice (WOA) which implies that novices are more likely to integrate robot advice in their decision making. This confirms the first hypothesis of this study and it proves that customer knowledge is an appropriate behavioural segmentation variable for the effective implementation of service robot counselling in the service encounter context because novices are willing to rely on service robot advice. This finding is in line with literature findings about algorithm appreciation (Logg, Minson & Moore, 2019) and algorithm aversion (Dietvorst, Simmons, & Massey, 2015). The underlying principle explaining this effect could be the relation between task's perceived difficulty and reliance on advice discovered by Gino and Moore (2006). As a matter of fact, when people perceive a certain task as difficult, they are more prone to seek for advice and integrate it (Gino & Moore, 2006). Alba and Hutcherson (1987) proved that when people develop expertise in a specific domain they improve and strengthen a set of cognitive tools needed for performance of tasks in that specific domain. As a consequence, experts develop a superior effectiveness and efficiency of decision making with respect to novices and this provokes a feeling called cognitive ease (Kahneman, 2011; Park & Lessing 1981). According to Kahneman (2011) this sensation provokes a perception of effortlessness of the task. As a consequence, novices, who are less likely to experience cognitive ease with respect to experts, may be more likely to rely on advice because they are more likely to perceive a task related to the service as complex.

In this regard, this study demonstrates an important finding concerning advice taking and accuracy of decision making. In fact, comparing the answers of novices and experts before and after receiving advice, it is clear that experts outperform novices before receiving advice in terms of accuracy of decision-making. In this study correct answer was shade 230 which, according to a make-up artist interviewed before designing the experiment, is the correct shade for matching the skin tone displayed in the pictures[1]. Before receiving advice, experts' ratio of correct answers is higher with respect to novices' ratio of correct answers. This is not surprising since prior literature demonstrated how superior expertise improves accuracy of decision-making because experts develop certain skills that facilitate and improve accuracy of decision-making (Alba & Hutcherson, 1987; Kahneman, 2011; Park & Lessing 1981). However, after participants receive robot advice, the situation changes dramatically. Indeed, after receiving the advice, novices' ratio of correct answers is higher with respect to experts' ratio of correct answers. This seemingly counterintuitive finding was previously demonstrated by Logg, Minson and Moore (2019) in the context of algorithm advice in a study investigating *algorithm appreciation*. According to Logg, Minson and Moore (2019) the reason for this effect is attributable to experts' overconfidence which leads them to experience what Dietvorst, Simmons and Massey (2015) termed as *algorithm aversion*. In fact, experts' tendency to overestimate their own judgement results in lower advice taking (Logg, Minson & Moore, 2019). This is true both when the advice comes from a human and an algorithm-based source (Dietvorst, Simmons, & Massey, 2015; Dawes, 1979; Dawes, Faust & Meehl, 1989; Yeomans, Shah, Mullainathan & Kleinberg). Thus, overconfidence is a key element explaining advice discounting (Logg, Minson & Moore, 2019; Healy & Moore, 2007). An explanation for novices' lower overconfidence can be attributed to higher perceived difficulty of the task which was proved by Gino and Moore (2006) to reduce overconfidence. However, not only novices have a higher tendency to integrate robot advice. This also influences accuracy of decision making such that novices manage to outperform experts' decision-making accuracy through their greater integration of robot advice. Similar results had been found by Logg, Minson and Moore (2019) in specific domains such as politics, economics, and law. However, this research demonstrates that the occurrence of this phenomenon is relevant also in consumer contexts.

Moreover, this research proves that there is also another element playing a key role in shaping the negative relation between customer knowledge and weight on advice: anticipated embarrassment. Indeed, the experiment conducted in this research proves that the effect of customer knowledge on weight on advice is conditionally mediated by anticipated embarrassment in the service encounter context. In fact, the experiment proved that customer knowledge significantly and negatively influences embarrassment and that embarrassment positively affects weight on robot advice such that part of the effect of customer knowledge on trust in robot advice is explained by an increase in anticipated embarrassment which increases reliance on robot advice. Moreover, this study proved that this effect is conditioned by robot anxiety, which decreases the effect of embarrassment on weight on advice. The fact that novices are more likely to experience and anticipate embarrassment in the service encounter context confirms the second hypothesis of this model and it is in line

[1]See appendix c, figure 1 - *Fondation shades – First choice and final choice* (FentyBeauty.com) and figure 2 - *Fondation shades – Robot advice* (FentyBeauty.com)

with findings of Miller (1996) who found a positive correlation between lack of knowledge and increased anticipation and perception of embarrassment.

Furthermore, the positive relation between anticipated embarrassment and weight on robot advice proved in this study confirms the third hypothesis of the model. This relation can be explained through a coping behaviour aimed at protecting individuals' self-image when they believe that it is at stake because of their lack of familiarity with the service or product. As a matter of fact, Baumeister et al. (2001) demonstrated that embarrassment is highly influential in shaping individuals' behaviour because people are highly motivated to preserve the usual image that they present of their self. Moreover, Grace (2007) empirically proved that avoidance of social interaction is a coping behaviour enacted in the service encounter. In fact, according to Miller (1996) a prerequisite for people to perceive and anticipate embarrassment is that they fear that other people they are interacting with (either directly or indirectly) may negatively evaluate them. Robot advisors, although able to create some kind of social presence (Mann et al. 2015; Wirtz et al, 2018), are unlikely to be perceived as conscious agents able to negatively evaluate customers (Gray, Gray & Wegner, 2007) and thus they are less likely to trigger embarrassment. As a consequence, a further explanation for novices' tendency to rely on algorithm-based advice and, in particular, robot advice, is attributable to a coping behaviour triggered by a desire to avoid social interactions. This is caused by anticipated embarrassment in the service encounter due to their lack of expertise and familiarity the product or service.

However, this study demonstrated that the extent to which embarrassment increases weight on robot advice depends on the extent to which people experience or anticipate robot anxiety in human-robot interactions. When people experience robot anxiety, the effect of embarrassment on weight on advice is dramatically reduced and this finding confirms the fourth hypothesis of this model. An explanation for this effect is that robot anxiety triggers a series of negative feelings and attitudes towards robots as well as an anxious state that spurs people to avoid robots and human-robot-interactions (de Graaf & Allouch, 2013). This fear and a sense of uncanniness were proved to have a negative influence on trust afforded to robots (Mathur & Reichling, 2016). Therefore, the reason for this effect can be attributed to a desire for robot-avoidance triggered by the fear and discomfort caused by the idea of interacting with the robot.

The last part of the model concerned the moderation of robot design of the moderation effect of robot anxiety on the mediation effect of embarrassment of the relation between customer knowledge and weight on the advice. In particular, the model of the study predicted that three types of designs moderated robot anxiety. The moderately anthropomorphized design was expected to decrease robot anxiety compared to the control condition (hypothesis 5a), the extremely anthropomorphized design was expected to increase robot anxiety (hypothesis 5b) and the cute design was expected to decrease robot anxiety (hypothesis 6). This study only confirms these hypotheses partially. Hypothesis 5a is not confirmed because the moderately anthropomorphized design did not exhibit substantial differences in terms of robot anxiety with respect to the control condition. Indeed, participants exposed to this condition as opposed to participants exposed to the control condition did experience slightly lower levels of robot anxiety, however this difference was not significant. When looking at the interaction between the effect of this design on the moderated mediation of the model the effect is positive as predicted but it is not significant. The very same pattern can be observed for the cute design which means that hypothesis 6 is not confirmed either. An explanation for these inconclusive results could be due to an effect discovered by Savela, Turja and Oksanen (2017) according to which participants in experiments overestimate the robot anxiety that they would experience in human-robot interactions. Indeed, participants that actually interact with a physical robot tend to report significantly lower levels of robot anxiety with respect to participants asked to imagine interacting with a robot. Looking at the average robot anxiety reported by the sample it is clear that most people were severely afraid of the robots regardless of their design. For practical reasons and the spread of SARS-CoV-2 (responsible for COVID-19) it was impossible to conduct this experiment with physically present participants and robots. However, it is possible that conducting the experiment online may have intensified anticipation of robot anxiety leading to biased results.

Moreover, because participants only had the possibility to see a short video of the robot rather than personally seeing it interacting with the surrounding environment, they may have not been able to fully appreciate the details of the robot nor they could engage with it. De facto Kuri is only 50 cm tall (Mayfield Robotics, 2020) while Cruzr is 1.5 m tall (UBTECH Robotics, 2020). These characteristics were proved to have a dramatic effect on perceived threat of the robot and consequent robot anxiety (Broadbent, 2017). However, because participants could only see a video of one robot, features such as body size may have gone unnoticed.

Another element that might have prevented these designs from effectively diminishing robot anxiety is the fact that the majority of the sample was made of women and women were proved to exhibit significantly higher levels of robot anxiety with respect to men by Reich and Eyssel (2013). Target customers of make-up and foundation are typically women, as a consequence the online experiment has been mostly distributed among women. However, because they tend to be more afraid of robots, it is possible that robot design did not manage to reduce such high levels of robot anxiety.

Another explanation could be related to the fact that robots shown may have not been perceived as different enough to justify different levels of robot anxiety. The pre-test of this study did demonstrate that these robots were perceived as expected, thus Kuri has been perceived as significantly cuter than Cruzr and Asimo has been perceived as significantly more anthropomorphized with respect to Cruzr. However, these differences may not have been great enough to change participants attitude towards Cruzr, Asimo and Kuri.

The only design that was proved to elicit a significant different level of robot anxiety was the extremely anthropomorphized one. Indeed, people exposed to the extremely anthropomorphized design exhibited significantly higher levels of robot anxiety confirming hypothesis 5b. However, when looking at the interactions between the effect of robot designs, robot anxiety and embarrassment on WOA the results are not significant. This means that extremely anthropomorphized designs do elicit higher levels of robot anxiety, however this effect is not substantial enough to influence weight on advice. The explanation for the increased robot anxiety generated by this kind of design is attributable to the *uncanny valley effect* according to which people have a preference for anthropomorphized design but they find extremely anthropomorphized designs to be creepy and this negatively affects trust afforded to such robots (Mori, 1970; Mori, MacDorman, & Kageki, 2012). However, because people could only see a video of the robot rather than physically interacting with it, they might have not felt engaged enough with it. It is possible that this inhibited the extent to which this kind of robot design has been influential in shaping trust in robot advice.

An unexpected finding that has a considerable effect on weight on advice is the interaction between embarrassment and the cute design which has a negative influence on weight on advice. What is extremely interesting about this finding is that when looking for separate influences on weight on advice of these two variables they are both positive. However, when combined, they negatively and significantly influence trust granted to the robot. It makes sense to think that the cute design could be construed as incompetent due to its resemblance to a toy or a naïve creature. In fact, cute design in service robots was proved to increase warmth of the machine due to the resemblance to kids (Nenkov & Scott, 2014 ; Caudwell, Lacey, & Sandoval, 2019), however, this may come at the expense of competence according to the *stereotype content model* (Fiske, Cuddy & Glick, 2007). This study demonstrated that people that experience and anticipate embarrassment the most in the service encounter are the ones unfamiliar with the product or service. As a consequence, it is possible that those people require the advisor to be or at least appear to be competent enough to guide their decision. It is possible that cute designs, or simply the cute design used in the experiment, do not convey such competence. The fact that the robot does not talk might have made people think that robot was going to be of little help in the service encounter. Another explanation comes from Caudwell, Lacey, and Sandoval (2019). In fact, in a work assessing the effect of cute designs on people's attitude towards robots they found that, in general, cute designs foster acceptance of robots because they increase engagement with the robot and the extent to which people are willing to interact with them (Caudwell, Lacey, & Sandoval, 2019). However, in instances in which cuteness of the design is perceived as irrelevant, cuteness may even be detrimental to positive attitudes towards the robot (Caudwell, Lacey, & Sandoval, 2019). It is possible that people anticipating embarrassment in the service encounter may perceive cuteness of the service robot as irrelevant because what they really seek for in an advisor is competence. Thus, this would explain why the combination of embarrassment and cute design does not work well for people anticipating embarrassment while the design itself does not negatively affect weight on advice.

This research contributes to existing literature in numerous ways. *Firstly*, it contributes to the literature on advice taking, judge-advisor systems and weight on algorithmic advice (Dawes, 1979; Dawes, Faust & Meehl, 1989; Yeomans et al. 2019; Buell & Norton, 2011) showing that effects comparable to the ones elicited by algorithms can be triggered by service robots. Indeed, prior literature on advice taking identified a suboptimal integration of external advice (Dawes, 1979; Dawes, Faust & Meehl, 1989; Yeomans et al. 2019) and this effect seems to be even amplified when the source of advice is algorithmic rather than human (Dietvorst, Simmons, & Massey, 2015). Indeed, algorithms have been proved to outperform humans in various tasks but despite this, humans have a tendency to distrust them (Dawes, 1979; Dawes, Faust & Meehl, 1989). This implies that humans miss the opportunity to improve accuracy of decision-making because they have a bias for discarding advice. As a consequence, it is crucial to identify factors that may lead to higher trust in external advice (Yeomans et al. 2019). Novices in this experiment reacted very positively to robot advice integrating it in their decision-making process and this suggests that the use of robots in the service context allows for great algorithmic advice compliance from this specific customer group.

Secondly, this work shows that findings about algorithm aversion (Dietvorst, Simmons, & Massey, 2015) and appreciation (Logg, Minson & Moore, 2019) apply to service robots as well, confirming that while novices exhibit higher reliance on algorithmic advice – whether the source is a physical robot or an virtual algorithm – experts exhibit lower reliance on algorithmic advice. In particular, one common finding of these apparently conflicting theories, namely experts' tendency to discard algorithmic advice, explains novices' greater tendency to comply to service robot's advice. Although Dietvorst, Simmons, and Massey (2015) are more sceptical concerning the extent to which people's decision-making can be influenced by algorithmic suggestions with respect to Logg, Minson and Moore (2019), they both agree that novices are less reluctant to integrate algorithmic advice in their decision-making process compared to experts. This research proved that implementing technology-based self-service strategy through service robots' recommendation is more effective for customers who have little expertise in the product or service. Thus, the current study bridged studies on algorithmic advice and robot advice.

Thirdly, this research shed a light on motivation for novices' higher increased reliance on algorithmic advice in the service encounter context that has never been investigated before. De facto, prior literature has identified experts' overconfidence to be the main determinant for such effect (Logg, Minson & Moore, 2019; Healy & Moore, 2007). However, this research proved that the conditional mediation of embarrassment of customer knowledge on WOA contributes to explain novices' greater weight on advice with respect to experts.

Fourthly, this study contributes to literature on embarrassment (Grace, 2007; Dahl, Manchanda & Argo, 2001) by identifying a new coping behaviour to avoid anticipated embarrassment: higher reliance on technology-based self-service in the form of service robots. This not only expands insights about consequences and determinants of embarrassment and anticipated embarrassment, but it also allows for a deeper understanding of how such factors facilitate acceptance of service robots.

Fifthly, this research proves that findings about embarrassment caused by the purchase of embarrassing products or service developed by Londono, Davies and Elms (2017) are applicable to instances in which embarrassment stems from perceptions of lack of knowledge of the product or service and thus it extends such findings to a broader variety of products and services.

Sixthly, the findings of this study expand literature about trust in robots and it achieves that through a method that had only been implemented for measuring reliance trust in algorithm, i.e. weight on advice. The application of Judge Advisor System (JAS) as well as weight on advice in the context of robot trust could deepen our understanding of what factors are key determinants in robot trust which have been proved to be crucial in affecting service robot acceptance (van Pinxteren et al. 2019). Moreover, although some papers analysed this variable (Mori, 1970; Mori, MacDorman, & Kageki, 2012; Mathur & Reichling, 2016; van Pinxteren et al. 2019) the majority of studies on robot acceptance focused on intention to use or actual use of service robots. It can be argued that the importance of trust in service robot and service robot advice is crucial because it affects the extent to which the service robot is able to influence customers' behaviour through compliance with advice. I argue that understanding what elements increase customers' trust in robots allows for a more effective use of service robots. Indeed, it is unpractical to focus on elements that increase intention to use and interact with the service robot neglecting elements that increase trust in its advice in the service context. Eventually, the goal of using service robots in customer care is supporting customers and influencing their purchasing behaviour. If trust in robot is not fostered, this objective cannot be achieved.

Seventhly, this research contributes to the understanding of the role of robot anxiety in diminishing trust in robot. In particular, it shows that robot anxiety can seriously harm efficacy of service robots through the diminishment of the positive relation between anticipated embarrassment and trust in robot. In other words, this paper bridges findings about anticipated embarrassment coping behaviours and the effect of robot anxiety.

Lastly, this research contributes to literature on robot designs as it proves that extremely anthropomorphized designs effectively elicit greater robot anxiety with respect to other kinds of robot designs.

This research also offers some insights that could guide managerial decisions concerning the implementation of an effective strategy for the use of robots in the service encounter. In a context in which companies are looking for solutions to limit the social interactions with employees due to the spread of COVID-19, the use of service robots could become even more relevant because they create social presence without being actual human beings. In order to pave the way for an effective and appropriate use of robots in the service encounter it is crucial to understand customer groups more likely to trust the robot advice, factors that undermine trust in robot advice and robot characteristics that reduce the effects of factors undermining robot trust. And this was exactly the focus of this research.

This work identifies a customer group that is highly prone to rely on service robot's advice: novice customers. Indeed, prior studies had identified several customer characteristics affecting service robot trust, acceptance, or intention to use. Among these we find demographic variables such as gender, age, education and field of occupation (Reich & Eyssel, 2013; de Graaf & Ben Allouch, 2013); social influence (de Graaf & Ben Allouch, 2013); personal traits like extroversion (Ivaldi et al, 2016) and sociability (de Graaf & Ben Allouch, 2013); dispositional traits associated with anthropomorphism (Reich & Eyssel, 2013); interest in technology and robots (Reich & Eyssel, 2013); robots anxiety (Reich & Eyssel, 2013; van Pinxteren, et al. 2019; Mende et al. 2019; de Graaf & Ben Allouch, 2013); and expectations of robot performance and required effort (de Graaf & Ben Allouch, 2013). Not only, this research contributes to these works from a theoretical point of view, but it also provides a useful managerial insight due to the fact that customer knowledge is a behavioural segmentation variable that is easily distinguishable through customer profiling with respect to variables identified by previous literature. This means that companies can easily identify what customers are more likely to positively react to service robots. This research shows that developing a strategy focusing on the implementation of service robots for targeting expert consumers may not work as well as a strategy aimed at engaging novice consumers.

Another managerial insight than can be drawn from this research is that service robots highly affect decision-making of consumers and this is extremely relevant in retail contexts in which consumers may feel overwhelmed by the variety of products available as in the beauty products retail context.

In addition to that, this work proves that a seemingly detrimental customer feeling such as anticipated embarrassment in the service encounter can be turned into a strength when the customer is provided with the possibility to avoid social interaction through technology-based self-service in the form of a service robot. Because anticipated embarrassment increases the extent to which consumers are willing to comply with the service robot's advice, this increases the efficacy of the machine and it improves the overall success of the strategy for the implementation of service robots. This means that company using service robots could develop an effective way for both diminishing anticipated discomfort of certain consumers while appropriately supporting them throughout their customer journey.

Another key insight is that companies that decide to implement such strategy should be aware of the level of robot anxiety experienced by target customers because this can seriously harm the efficacy of the strategy. A proxy for estimating that would be considering whether target customers exhibit features that were proved to be negatively correlated with robot anxiety such as education, gender, nationality etc… (Reich & Eyssel, 2013).

Lastly, this research partially confirmed findings concerning the effect of design on robot anxiety and it proves that extremely anthropomorphized designs are to be avoided because they trigger a feeling of uncanniness in consumers, diminishing the extent to which they are willing to trust them.

This study has some limitations and it offers opportunity for further research. For instance, this study was conducted through an online experiment. This was due to practical limitations and the impossibility to collect data in physical lab experiment or, even better, in a real service encounter with real service robots. However, Savela, Turja and Oksanen (2017) proved that conducting in lab or on the field real experiments lead to substantially different results when it comes to robot anxiety. Further research could replicate this experiment in such conditions to verify actual robot anxiety and how it is different from self-reported robot anxiety.

Another limitation of this study concerns the sample selected, as a matter of fact, in order to gain significant insights about the beauty industry the sample has been selected to match target customers for make-up products. Thus, because such items are predominantly used by women, the sample of this study was mainly made of women. However, as it was demonstrated by Reich and Eyssel (2013) this group has a tendency to exhibit higher levels of robot anxiety. As a consequence, replicating this experiment in a different industry which targets both men and women may lead to different results. Future research could investigate this matter.

Moreover, this experiment only tested four designs that may have been perceived similar by respondents, future research could test for different designs or even same design kinds but with different robots to test for this effect. For instance, this study did not investigate the role of physical presence on weight on advice because to measure the effect of such a feature the experiment was required to be conducted in a physical lab with physical and non-physical robots. Further studies could address this question. Moreover, van Pinxteren, et al. (2019) proved that different kinds of anthropomorphic cues have different effect on people's willingness to trust robots. This is was also proved to be influenced by discomfort caused by the robot such that participants experiencing high discomfort in HRI were demonstrated to prefer robots that behave like human-beings while people experiencing low levels of robot anxiety were proved to prefer robots that look like human beings (van Pinxteren et al. 2019). Future research could investigate whether discomfort caused by anticipated embarrassment triggers a similar effect.

Lastly, this study did not focus on characteristics such as perceived warmth and competence of robots and the combination of perception of such features and embarrassment. Future research could test that and verify if that is the reason why cute design combined with embarrassment was proved to decrease the level of trust afforded to that specific robot.

REFERENCES

Aggarwal, P., & McGill, A. (2007). Is That Car Smiling at Me? Schema Congruity as a Basis for Evaluating Anthropomorphized Products. *Journal Of Consumer Research,* 34(4), 468-479. doi: 10.1086/518544

Alba, J., & Hutchinson, J. (1987). Dimensions of Consumer Expertise. *Journal Of Consumer Research,* 13(4), 411. doi: 10.1086/209080

Altmann, J., & Sauer, F. (2017). Autonomous Weapon Systems and Strategic Stability. *Survival*, *59*(5), 117-142. doi: 10.1080/00396338.2017.1375263

Askarpour, M., Mandrioli, D., Rossi, M., & Vicentini, F. (2019). Formal model of human erroneous behavior for safety analysis in collaborative robotics. *Robotics And Computer-Integrated Manufacturing*, *57*, 465-476. doi: 10.1016/j.rcim.2019.01.001

Baumeister, R., Bratslavsky, E., Finkenauer, C., & Vohs, K. (2001). Bad is Stronger than Good. *Review Of General Psychology*, 5(4), 323-370. doi: 10.1037/1089-2680.5.4.323

Bettman, J., & Park, C. (1980). Effects of Prior Knowledge and Experience and Phase of the Choice Process on Consumer Decision Processes: A Protocol Analysis. *Journal Of Consumer Research*, 7(3), 234. doi: 10.1086/208812

Broadbent, E. (2017). Interactions With Robots: The Truths We Reveal About Ourselves. *Annual Review Of Psychology*, 68(1), 627-652. doi: 10.1146/annurev-psych-010416-043958

Broadbent, E., Kumar, V., Li, X., Sollers, J., Stafford, R., MacDonald, B., & Wegner, D. (2013). *Robots with Display Screens: A Robot with a More Humanlike Face Display Is Perceived To Have More Mind and a Better Personality*. Plos ONE, 8(8), e72589. doi: 10.1371/journal.pone.0072589

Brosnan, M. (2002). Technophobia: *The Psychological Impact of Information Technology*. London: Routledge.

Brucks, M. (1985). The Effects of Product Class Knowledge on Information Search Behavior. *Journal Of Consumer Research*, 12(1), 1. doi: 10.1086/209031

Buell, R., & Norton, M. (2011). The Labor Illusion: How Operational Transparency Increases Perceived Value. *Management Science*, *57*(9), 1564-1579. doi: 10.1287/mnsc.1110.1376

Carpinella, C., Wyman, A., Perez, M., & Stroessner, S. (2017). The Robotic Social Attributes Scale (RoSAS). *Proceedings Of The 2017 ACM/IEEE International Conference On Human-Robot Interaction*. doi: 10.1145/2909824.3020208

Casey, M., Stewart, D., & Wigginton, C. (2020). Robots on the move: Professional service robots set for double-digit growth. Retrieved 28 March 2020, from https://www2.deloitte.com/global/en/insights/industry/technology/technology-media-and-telecom-predictions/2020/professional-service-robots.html

Caudwell, C., Lacey, C., & Sandoval, E. (2019). The (Ir)relevance of Robot Cuteness. Proceedings Of The 31St Australian Conference On Human-Computer-Interaction. doi: 10.1145/3369457.3369463

Chandler, J., & Schwarz, N. (2010). Use does not wear ragged the fabric of friendship: Thinking of objects as alive makes people less willing to replace them. *Journal of Consumer Psychology*, 20, 138–145. doi: 10.1016/j.jcps.2009.12.008

Chase, W., & Simon, H. (1973). Perception in chess. *Cognitive Psychology*, *4*(1), 55-81. doi: 10.1016/0010-0285(73)90004-2

Dagger, T., & Sweeney, J. (2007). Service Quality Attribute Weights - How Do Novice and Longer-Term Customers Construct Service Quality Perceptions?. *Journal Of Service Research*, 10(1), 22-42. doi: 10.1177/1094670507303010

Dahl, D., Manchanda, R., & Argo, J. (2001). Embarrassment in Consumer Purchase: The Roles of Social Presence and Purchase Familiarity. *Journal Of Consumer Research*, 28(3), 473-481. doi: 10.1086/323734

Dawes, R. (1979). The robust beauty of improper linear models in decision making. *American Psychologist*, *34*(7), 571-582. doi: 10.1037/0003-066x.34.7.571

Dawes, R., Faust, D., & Meehl, P. (1989). Clinical versus actuarial judgment. *Science*, *243*(4899), 1668-1674. doi: 10.1126/science.2648573

de Graaf, M., & Ben Allouch, S. (2013). Exploring influencing variables for the acceptance of social robots. Robotics And Autonomous Systems, 61(12), 1476-1486. doi: 10.1016/j.robot.2013.07.007

Demeure, V., Niewiadomski, R., & Pelachaud, C. (2011). How Is Believability of a Virtual Agent Related to Warmth, Competence, Personification, and Embodiment?. *Presence: Teleoperators And Virtual Environments*, 20(5), 431-448. doi: 10.1162/pres_a_00065

DeNisco Rayome, A. (2018). How Sephora is leveraging AR and AI to transform retail and help customers buy cosmetics. Retrieved 17 April 2020, from https://www.techrepublic.com/article/how-sephora-is-leveraging-ar-and-ai-to-transform-retail-and-help-customers-buy-cosmetics/

Devlin, J. (2011). Evaluative cues and services: the effect of consumer knowledge. *Journal Of Marketing Management*, 27(13-14), 1366-1377. doi: 10.1080/0267257x.2011.624533

Dietvorst, B., Simmons, J., & Massey, C. (2015). Algorithm aversion: People erroneously avoid algorithms after seeing them err. *Journal Of Experimental Psychology*: General, 144(1), 114-126. doi: 10.1037/xge0000033

Epley, N., Waytz, A., & Cacioppo, J. (2007). On seeing human: A three-factor theory of anthropomorphism. *Psychological Review*, 114(4), 864-886. doi: 10.1037/0033-295x.114.4.864

FentyBeauty.com. (2020). Fenty Beauty - PRO FILT'R SOFT MATTE LONGWEAR FOUNDATION. Retrieved 6 May 2020, from https://www.fentybeauty.com/pro-filtr-soft-matte-longwear-foundation/FB30006.html

Fiske, S., Cuddy, A., & Glick, P. (2007). Universal dimensions of social cognition: warmth and competence. *Trends In Cognitive Sciences*, 11(2), 77-83. doi: 10.1016/j.tics.2006.11.005

Fogg, B., & Nass, C. (1997). How users reciprocate to computers. *CHI '97 Extended Abstracts On Human Factors In Computing Systems Looking To The Future* - CHI '97. doi: 10.1145/1120212.1120419

Gilovich, T., & Savitsky, K. (1999). The Spotlight Effect and the Illusion of Transparency. *Current Directions In Psychological Science*, *8*(6), 165-168. doi: 10.1111/1467-8721.00039

Gino, F., & Moore, D. (2006). Effects of task difficulty on use of advice. *Journal Of Behavioral Decision Making*, *20*(1), 21-35. doi: 10.1002/bdm.539

Grace, D. (2007). How Embarrassing! An Exploratory Study of Critical Incidents Including Affective Reactions. *Journal Of Service Research,* 9(3), 271-284. doi: 10.1177/109467050700900305

Gray, H., Gray, K., & Wegner, D. (2007). Dimensions of Mind Perception. *Science,* 315(5812), 619-619. doi: 10.1126/science.1134475

Grewal, D., Noble, S., Roggeveen, A., & Nordfalt, J. (2019). The future of in-store technology. *Journal Of The Academy Of Marketing Science*, *48*(1), 96-113. doi: 10.1007/s11747-019-00697-z

Hanson Robotics. (2020). *Hanson Robotics - Sophia* [Image]. Retrieved from https://www.hansonrobotics.com/sophia/

Hayes, A. (2017). Partial, conditional, and moderated moderated mediation: Quantification, inference, and interpretation. *Communication Monographs*, *85*(1), 4-40. doi: 10.1080/03637751.2017.1352100

Healy, P., & Moore, D. (2007). The Trouble With Overconfidence. *SSRN Electronic Journal*. doi: 10.2139/ssrn.1001821

Hellén, K., & Sääksjärvi, M. (2013). Development of a scale measuring childlike anthropomorphism in products. *Journal Of Marketing Management*, *29*(1-2), 141-157. doi: 10.1080/0267257x.2012.759989

Higuchi, M., & Fukada H. (2002), *"A Comparison of Four Causal Factors of Embarrassment in Public and Private Situations," The Journal of Psychology*, 136 (4), 399-406.

Hinks, T. (2020). Fear of Robots and Life Satisfaction. *International Journal Of Social Robotics*. doi: 10.1007/s12369-020-00640-1

Hoa, T., & Cabibihan, J. (2012). Cute and soft. *Proceedings Of The Workshop At SIGGRAPH Asia On - WASA* '12. doi: 10.1145/2425296.2425310

Hoffman, G., Forlizzi, J., Ayal, S., Steinfeld, A., Antanitis, J., & Hochman, G., Hochendoner, E., & Finkenaur, J. (2015). Robot Presence and Human Honesty. *Proceedings Of The Tenth Annual ACM/IEEE International Conference On Human-Robot Interaction* - HRI '15. doi: 10.1145/2696454.2696487

Honda. (2020). *Honda - Asimo* [Image]. Retrieved from https://asimo.honda.com/

Huang, M., & Rust, R. (2017). Technology-driven service strategy. *Journal Of The Academy Of Marketing Science*, *45*(6), 906-924. doi: 10.1007/s11747-017-0545-6

Ivanov, S. and Webster, C. (2019), Conceptual framework of the use of robots, artificial intelligence and service automation in travel, tourism, and hospitality companies. *Robots, Artificial Intelligence and Service Automation in Travel, Tourism and Hospitality*, ISBN: 978-1-78756-688-0, Emerald Publishing, London.

Ivaldi, S., Lefort, S., Peters, J., Chetouani, M., Provasi, J., & Zibetti, E. (2016). Towards Engagement Models that Consider Individual Factors in HRI: On the Relation of Extroversion and Negative Attitude Towards Robots to Gaze and Speech During a Human–Robot Assembly Task. *International Journal Of Social Robotics*, 9(1), 63-86. doi: 10.1007/s12369-016-0357-8

Kahneman, D. (2011). *Thinking, fast and slow.* New York, NY: Farrar, Straus and Giroux.

Kidd, C., & Breazeal, C. (2008). Robots at home: Understanding long-term human-robot interaction. *2008 IEEE/RSJ International Conference On Intelligent Robots And Systems*. doi: 10.1109/iros.2008.4651113

Kinard, B., Capella, M., & Kinard, J. (2009). The Impact of Social Presence on Technology Based Self-Service Use: The Role of Familiarity. *Services Marketing Quarterly*, 30(3), 303-314. doi: 10.1080/15332960902993593

Knijnenburg, B., Reijmer, N., & Willemsen, M. (2011). Each to his own. *Proceedings Of The Fifth ACM Conference On Recommender Systems* - Recsys '11. doi: 10.1145/2043932.2043960

Krueger, J. (2003). Return of the ego--Self-referent information as a filter for social prediction: Comment on Karniol (2003). *Psychological Review*, *110*(3), 585-590. doi: 10.1037/0033-295x.110.3.585

L'Oréal.com. (2020). L'Oréal Unveils Perso, The World's First AI-Powered Device For Skincare And Cosmetics - L'Oréal Group | World Leader in Beauty | Official Website. Retrieved 17 April 2020, from https://www.loreal.com/media/news/2020/january/perso-ces-innovation

Leroi-Werelds, S. (2019). An update on customer value: state of the art, revised typology, and research agenda. *Journal Of Service Management, 30*(5), 650-680. doi: 10.1108/josm-03-2019-0074

Lindner, Evelin G. (2001), *"Humiliation and the Human Condition: Mapping a Minefield,"* Human Rights Review, 2 (2), 46-63.

Logg, J., Minson, J., & Moore, D. (2019). Algorithm appreciation: People prefer algorithmic to human judgment. *Organizational Behavior And Human Decision Processes*, 151, 90-103. doi: 10.1016/j.obhdp.2018.12.005

Londono, J., Davies, K., & Elms, J. (2017). Extending the Theory of Planned Behavior to examine the role of anticipated negative emotions on channel intention: The case of an embarrassing product. *Journal Of Retailing And Consumer Services*, 36, 8-20. doi: 10.1016/j.jretconser.2016.12.002

MacDorman, Karl F. (2005), "Mortality Salience and the Uncanny Valley," in Humanoid Robots, *2005 5th IEEE-RAS International Conference*, 399–405.

Mahroof, K. (2019). A human-centric perspective exploring the readiness towards smart warehousing: The case of a large retail distribution warehouse. *International Journal Of Information Management, 45*, 176-190. doi: 10.1016/j.ijinfomgt.2018.11.008

Mann, J., MacDonald, B., Kuo, I., Li, X., & Broadbent, E. (2015). People respond better to robots than computer tablets delivering healthcare instructions. *Computers In Human Behavior*, 43, 112-117. doi: 10.1016/j.chb.2014.10.029

Mathur, M., & Reichling, D. (2016). Navigating a social world with robot partners: A quantitative cartography of the Uncanny Valley. *Cognition*, 146, 22-32. doi: 10.1016/j.cognition.2015.09.008

Mayfield Robotics. (2020). *https://www.heykuri.com/explore-kuri/* [Image].

Mende, M., Scott, M., van Doorn, J., Grewal, D., & Shanks, I. (2019). Service Robots Rising: How Humanoid Robots Influence Service Experiences and Elicit Compensatory Consumer Responses. *Journal Of Marketing Research*, 56(4), 535-556. doi: 10.1177/0022243718822827

Miller, R. S. (1996). Embarrassment: Poise and peril in everyday life. New York: Guilford Press.

Mittal, V., Kumar, P., & Tsiros, M. (1999). Attribute-Level Performance, Satisfaction, and Behavioral Intentions over Time: A Consumption-System Approach. *Journal Of Marketing*, 63(2), 88-101. doi: 10.1177/002224299906300206

Moon, Y. (2000). Intimate Exchanges: Using Computers to Elicit Self-Disclosure From Consumers. *Journal Of Consumer Research*, 26(4), 323-339. doi: 10.1086/209566

Moore, S., Dahl, D., Gorn, G., & Weinberg, C. (2006). Coping with condom embarrassment. *Psychology, Health & Medicine*, *11*(1), 70-79. doi: 10.1080/13548500500093696

Mori M. (1970). *The uncanny valley*. Energy 7:33–35

Mori, M., MacDorman, K., & Kageki, N. (2012). The Uncanny Valley [From the Field]. *IEEE Robotics & Automation Magazine,* 19(2), 98-100. doi: 10.1109/mra.2012.2192811

Nass, C., & Moon, Y. (2000). Machines and Mindlessness: Social Responses to Computers. *Journal Of Social Issues*, 56(1), 81-103. doi: 10.1111/0022-4537.00153

Nass, C., Moon, Y., & Green, N. (1997). Are Machines Gender Neutral? Gender-Stereotypic Responses to Computers With Voices. *Journal Of Applied Social Psychology*, 27(10), 864-876. doi: 10.1111/j.1559-1816.1997.tb00275.x

Nelson, P. (1970). Information and Consumer Behavior. *Journal Of Political Economy*, *78*(2), 311-329. doi: 10.1086/259630

Nenkov, G., & Scott, M. (2014). "So Cute I Could Eat It Up": Priming Effects of Cute Products on Indulgent Consumption. *Journal Of Consumer Research*, 41(2), 326-341. doi: 10.1086/676581

Niewiadomski, R., Demeure, V., & Pelachaud, C. (2010). Warmth, Competence, Believability and Virtual Agents. Intelligent Virtual Agents, 272-285. doi: 10.1007/978-3-642-15892-6_29

Nomura, T., Suzuki, T., Kanda, T., & Kato, K. (2006). Measurement of Anxiety toward Robots. ROMAN 2006 - *The 15Th IEEE International Symposium On Robot And Human Interactive Communication.* doi: 10.1109/roman.2006.314462

P&G.com. (2019). Retrieved 20 April 2020, from https://news.pg.com/sites/pg.newshq.businesswire.com/files/fact_sheet/file/Opte_Fact_Sheet.pdf

Park, C., & Lessig, V. (1981). Familiarity and Its Impact on Consumer Decision Biases and Heuristics. *Journal Of Consumer Research*, 8(2), 223. doi: 10.1086/208859

Rao, A., & Monroe, K. (1988). The Moderating Effect of Prior Knowledge on Cue Utilization in Product Evaluations. *Journal Of Consumer Research*, 15(2), 253. doi: 10.1086/209162

Reich, N., & Eyssel, F. (2013). Attitudes towards service robots in domestic environments: The role of personality characteristics, individual interests, and demographic variables. Paladyn, *Journal Of Behavioral Robotics*, 4(2). doi: 10.2478/pjbr-2013-0014

Sabelli, A., & Kanda, T. (2015). Robovie as a Mascot: A Qualitative Study for Long-Term Presence of Robots in a Shopping Mall. *International Journal Of Social Robotics*, 8(2), 211-221. doi: 10.1007/s12369-015-0332-9

Savela, N., Turja, T., & Oksanen, A. (2017). Social Acceptance of Robots in Different Occupational Fields: A Systematic Literature Review. *International Journal Of Social Robotics*, *10*(4), 493-502. doi: 10.1007/s12369-017-0452-5

Siegel, M., Breazeal, C., & Norton, M. (2009). Persuasive Robotics: The influence of robot gender on human behavior. *2009 IEEE/RSJ International Conference On Intelligent Robots And Systems*. doi: 10.1109/iros.2009.5354116

Smith, D., & Park, C. (1992). The Effects of Brand Extensions on Market Share and Advertising Efficiency. *Journal Of Marketing Research*, *29*(3), 296. doi: 10.2307/3172741

SoftBank Robotics. (2020). *SoftBank Robotics - Pepper* [Image]. Retrieved from https://softbankrobotics.com/us/pepper

Sprengelmeyer, R., Perrett, D., Fagan, E., Cornwell, R., Lobmaier, J., & Sprengelmeyer, A. et al. (2009). The Cutest Little Baby Face. *Psychological Science*, 20(2), 149-154. doi: 10.1111/j.1467-9280.2009.02272.

Stanovich, K., & West, R. (2000). Individual differences in reasoning: Implications for the rationality debate?. *Behavioral And Brain Sciences*, 23(5), 645-665. doi: 10.1017/s0140525x00003435

Statista. (2019). Robotics - A Statista dossier on the global robotics market and application areas. Retrieved 17 April 2020, from https://www.statista.com/study/64326/robotics/

Thomas, D. (2019). Five tech trends shaping the beauty industry. Retrieved 17 April 2020, from https://www.bbc.com/news/business-48369970

Tversky, A., & Kahneman, D. (1974). Judgment under Uncertainty: Heuristics and Biases. *Science*, 185(4157), 1124-1131. doi: 10.1126/science.185.4157.1124

UBTECH Robotics. (2020). *UBTECH Robotics - Cruzr* [Image]. Retrieved from https://www.ubtrobot.com/products/cruzr

Uzzi, B. (2019). How Olay's AI-Powered Consultation Disrupts The Cosmetics Industry. Retrieved 17 April 2020, from https://www.forbes.com/sites/brianuzzi/2019/05/01/how-olays-ai-powered-consultation-disrupts-the-cosmetics-industry/#1fb2bda93e06

van Pinxteren, M., Wetzels, R., Rüger, J., Pluymaekers, M., & Wetzels, M. (2019). Trust in humanoid robots: implications for services marketing. *Journal Of Services Marketing*, 33(4), 507-518. doi: 10.1108/jsm-01-2018-0045

Wainer, J., Feil-seifer, D., Shell, D., & Mataric, M. (2006). The role of physical embodiment in human-robot interaction. ROMAN 2006 - *The 15Th IEEE International Symposium On Robot And Human Interactive Communication*. doi: 10.1109/roman.2006.314404

Walkington, C., & Bernacki, M. (2018). Personalizing Algebra to Students' Individual Interests in an Intelligent Tutoring System: Moderators of Impact. *International Journal Of Artificial Intelligence In Education*, *29*(1), 58-88. doi: 10.1007/s40593-018-0168-1

Waytz, A., & Norton, M. (2014). Botsourcing and outsourcing: Robot, British, Chinese, and German workers are for thinking—not feeling—jobs. *Emotion*, 14(2), 434-444. doi: 10.1037/a0036054

Waytz, A., Heafner, J., & Epley, N. (2014). The mind in the machine: Anthropomorphism increases trust in an autonomous vehicle. *Journal Of Experimental Social Psychology*, 52, 113-117. doi: 10.1016/j.jesp.2014.01.005

Wirtz, J., Patterson, P., Kunz, W., Gruber, T., Lu, V., Paluch, S., & Martins, A. (2018). Brave new world: service robots in the frontline. *Journal Of Service Management*, 29(5), 907-931. doi: 10.1108/josm-04-2018-0119

Xiong, Y., Peng, C., Grimstad, L., From, P., & Isler, V. (2019). Development and field evaluation of a strawberry harvesting robot with a cable-driven gripper. *Computers And Electronics In Agriculture*, *157*, 392-402. doi: 10.1016/j.compag.2019.01.009

Yaniv, I., & Kleinberger, E. (2000). Advice Taking in Decision Making: Egocentric Discounting and Reputation Formation. *Organizational Behavior And Human Decision Processes*, *83*(2), 260-281. doi: 10.1006/obhd.2000.2909

Yeomans, M., Shah, A., Mullainathan, S., & Kleinberg, J. (2019). Making sense of recommendations. *Journal Of Behavioral Decision Making*, *32*(4), 403-414. doi: 10.1002/bdm.2118