THÈSE

En vue de l'obtention du

DOCTORAT DE L'UNIVERSITE DE TOUTOUSE

Délivré par l'Université Toulouse Capitole

École doctorale : **Sciences de Gestion**

Présentée et soutenue publiquement par

Giulia PAVONE

Le **03/12/2021**

Using and Interacting with AI-Based Intelligent Technologies: Practical Applications on Autonomous Cars and Chatbots

---

Discipline : **Sciences de Gestion**

Spécialité : **Marketing**

Unité de recherche : **TSM Research, UMR 5303 CNRS**

Directeurs de thèse :

Monsieur Lars MEYER-WAARDEN, Professeur, Université Toulouse 1 Capitole

Monsieur Andreas MUNZEL, Professeur, Université Toulouse 1 Capitole

JURY

Rapporteurs Monsieur Polymeros CHRYSOCHOU, Professeur, Aarhus University
Monsieur Gilles N'GOALA, Professeur, Université de Montpellier
Madame Chiara ORSINGHER, Professeure, Alma Mater Studiorum-University of Bologna

Suffragante Madame Sandra LAPORTE, Professeure, Université Toulouse 1 Capitole

« L’université n’entend ni approuver ni désapprouver les opinions particulières de l’auteur. »

Table of Contents

List of Tables

List of Figures

Acknowledgments

Firstly, I would like to express my deepest gratitude to my supervisors Pr. Lars Meyer-Waarden and Pr. Andreas Munzel for their continuous support during my PhD. Your guidance was extremely important to advance during these years of research.

I would also like to extend my sincere thanks to the external examiners who have kindly accepted to review my PhD dissertation: Pr. Chrysochou, Pr. N'Goala and Pr. Orsingher. I am also deeply grateful to Pr. Sandra Laporte for accepting to take part in my PhD defence committee and for her insightful feedback during these years. My sincere thanks also go to Pr. Marc Kuhn, who hosted me in his research lab in ZEF, DHBW in Stuttgart, and all his research team. I am grateful for our collaboration, which was a great opportunity to grow as a researcher. I would also like to thank Dr. Julien Cloarec, for sharing his knowledge and for all his precious advices. Thanks also to Pr. Massara, who encouraged me to start the PhD when I was still a Master student.

I would also like to thank the marketing department of TSM for their precious feedback during the "Ateliers Axe Marketing". In addition, I would like to thank all the PhD colleagues of TSM. In particular, thanks to Camille and Eugénie for sharing these years and for all the insightful discussions about research. Thanks also to Dr. Marius Huber (DHBW) for conducting together the studies on autonomous cars and to Snežana for welcoming me in Stuttgart.

Thanks also to the administrative staff of TSM, for all their work and support.

Finally, yet very importantly, I would like to thank François for encouraging me during all these years and my family for their unwavering support.

Introduction

PART I
Defining AI in Marketing

Chapter 1. Artificial Intelligence in Marketing Research: Scientometric, TCCM Review and a Research Agenda

PART II
Practical AI Applications

Chapter 2. Rage Against the Machine: Investigating Consumers Negative Emotions, Attributions of Responsibility and Coping Strategies in AI-Based Service Failures

Chapter 3. Now, Take your Hands from the Steering Wheel! How Trust, Well-Being and Privacy Concerns Influence Intention to Use Semi- and Fully Autonomous Cars

PART III
On the Ethics of AI

Chapter 4. Consumers' Perspectives on AI Ethics and Trust: an Explorative Investigation of Ethical Concerns Towards Autonomous Cars and Chatbots

Overall Theoretical, Methodological, Managerial Contributions, Research Limits and Future Research Directions

INTRODUCTION

“The future is ours to shape. We are in a race that we need to win. It’s a race between the growing power of the technology and the growing wisdom we need to manage it.”

Max Tegmark

Professor of Physics, MIT

In the era of Anthropocene, Artificial Intelligence (AI) is often considered as one of the most promising and disruptive innovation of our times. The term AI is used to describe machines that mimic human cognitive functions such as learning, understanding, reasoning or problem-solving (Russell and Norvig 1995). Despite there are not unanimous definitions, AI can be referred to as “a system’s ability to interpret external data correctly, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation” (Kaplan and Haenlein 2019, p. 5). For a long time, an extensive narrative in popular culture has fantasised over the potential applications of artificial intelligence, often presenting it as uncanny intelligent robots, able to experience emotions, with a soul and a conscience (Kaplan and Haenlein 2019). Despite this type of artificial intelligence, defined as “General” or “Strong” AI, is still far from reality; a different, yet real form of AI has gradually entered individuals’ daily life: the artificial narrow intelligence.

Artificial Narrow Intelligence (ANI), also defined as “weak” AI, refers to those systems that can perform one or a few specific tasks and operate within a predefined environment (Davenport et al. 2020; Haenlein and Kaplan 2019). Examples of weak AI are those exploited by conversational agents or virtual assistants such a Siri and Alexa, recommendation systems, image recognition systems, face identification or self-driving cars (Kaplan and Haenlein 2019).

Artificial General Intelligence (AGI) or "Strong" AI refers instead to machines that exhibit all the aspects of human intelligence, performing any intellectual task normally accessible only to human beings (Davenport et al. 2020; Kaplan and Haenlein 2019). Besides AGI, researchers also suggest the possibility of a third generation of AI: the Artificial Superintelligence (ASI). ASI refers to that intelligence that is able to surpass humans in all aspects, from creativity to general wisdom and problem-solving (Bostrom 2014; Haenlein and Kaplan 2019). Both General AI and Super AI are still at a hypothetical level. Despite decades of setbacks, the development of General Intelligence remains a possibility both for the AI research community and for society at large (Baum et al. 2011). However as experts in the field hold a rich diversity of views, it is still difficult to make predictions about the future of AGI (Baum et al. 2011).

1. A Brief History of AI

In 1943, Warren McCulloch and Walter Pitts published one of the first seminal papers where, for the first time, the concepts of logical neurons and neural networks were introduced (McCulloch and Pitts 1943). However, it is in 1950 that the field of artificial intelligence took an important turn, when Alan Turing published the milestone paper "Computing machinery and intelligence", where the researcher considered the fundamental question "Can machines think?" (Turing 1950). Turing proposed a game known as the Turing test, the first experiment to measure machine intelligence. According to the test, a machine can be said to be intelligent when is able to conduct a conversation indistinguishable from a conversation with a human being. Almost at the same time, two graduate students in the Princeton mathematics department, Marvin Minsky and Dean Edmonds, built the first neural network computer in

1951. Nevertheless, we need to wait the Dartmouth Conference in 1956 to be able to talk about artificial intelligence. In fact, in this occasion McCarthy coined the term "artificial intelligence," which became the name of the scientific field.

For the next two decades, institutions and government started to heavily finance research on AI (Buchanan 2005; Haenlein and Kaplan 2019). Thus, innovations started to advance: one of the most successful examples is the well-known ELIZA, a computer program created between 1964 and 1966 by Joseph Weizenbaum at MIT, able to use natural language processing to simulate a conversation with a human. ELIZA was also one of the first programs capable of attempting to pass the Turing Test, as well one of the first prototypes of chatbots in the history of AI. However, during the late 70s research on AI started to slow down. In fact, both academics and institutions started to question the effective potential of the new field of AI to reach an advanced, real level of intelligence. In this regard, according to Kaplan and Haenlein (2019) one reason for the initial lack of progress in the field of AI lies in the way systems such as ELIZA tried to replicate human intelligence. Specifically, they were expert systems: collections of rules according to which human intelligence can be reconstructed in a top-down approach, in particular following "if-then" rules. The limitation of expert systems, however, is that they cannot be trained to interpret external data correctly and to learn from such data, not being able to adapt to different contexts and situations. The need to go beyond if-then rules lead to the creation of the artificial neural networks and deep learnings, which today form the basis of most applications such as image recognition algorithms used by Facebook, speech recognition algorithms used by conversational agents, computer visions and deep learning algorithms used by self-driving cars. Thus, in the late 80es and early 90ties, research began to increase again and many of the landmark goals of artificial intelligence started to be achieved. For instance, the first self-sufficient autonomous car appeared in the 1986, with Carnegie Mellon University's Navlab and ALV. In 1997, IBM's Deep Blue became the first computer to beat a chess champion when it defeated Russian grandmaster Garry Kasparov and in 2014, a chatbot called Eugene Goostman passed the Turing test.

2. Research Motivation

Interest in AI boomed in the 21st century, with the advances of deep learning, the introduction of faster computers and the augmented production and usage of data (Buchanan 2005). Many investors, companies, institutions and researchers have started to focus on the development of AI (Buchanan 2005). Besides them, also consumers, citizens and individuals have started to use AI applications in their daily life routine, conscientiously or not. Thus, AI represents today a huge business opportunity. In fact, revenues from the global artificial intelligence market are forecasted to see rapid growth in the coming years, reaching more than half a trillion U.S. dollars by 2024 (Statista 2021a).

According to one recent survey conducted among business leaders, one of the areas in which AI is mostly applied is marketing (MIT Technology Review Insights 2020). However, despite the huge increased investments and applications of AI, consumers seem to remain skeptics. In this regard, many surveys have been conducted, showing that consumers still not trust AI technology, in particular when the decision-making process is involved (Statista 2021c). In this scenario, it has become widely recognized the need of investigating and better comprehending how consumers are going to interact with and use these new intelligent technological products in their daily routine. However, as the applications of artificial intelligence are vast and numerous, a strategical decision over the focus of analysis is imperative. In this regard, two of the most discussed AI applications which are defining the future of AI technology in marketing and consumer behaviors research are conversational agents such as chatbots, and autonomous vehicles (Davenport et al. 2020; Grewal et al. 2020;

Hengstler et al. 2016). In fact, both technologies represent a huge market opportunity, being progressively implemented in society and becoming part of consumers' life. In particular, the chatbot market is expected to reach 23 billion US Dollar in 2027 (PwC 2021). America and Asia Pacific represent the main markets (63% of total) but stronger growth is expected in Europe and Russia (PwC 2021). In this regard, chatbots and intelligent virtual assistant are the solutions with the potential highest rate of diffusion and with the highest expected future adoption (PwC 2021). On the other hand, the public discussion around the introduction of autonomous cars is becoming the more and more urgent. In fact, the autonomous car market represents also an important business opportunity, which is expected to reach a size of over 37 billion U.S. dollars already by 2023 (Statista 2021b).

Besides the business value, also the intrinsic nature of these two different types of AI applications offers interesting reasons to investigate them. In this regard, as suggested by Hengstler et al. (2016) and Du and Xie (2020) autonomous cars and conversational agents have some point in common and some differences which might help researchers to grasp different aspects of AI. First, if on the one hand they both contain a component of AI (Hengstler et al. 2016), on the other hand they differ on the type of AI technique used and their level of intelligence (Du and Xie 2020). In particular, chatbots mainly use Machine Learning (ML) and Natural Language Processing (NLP) to be able to verbally interact; autonomous vehicles mainly use computer visions and Deep Learning (DL) to be able to detect and process information in the surrounding environment.

Second, both technologies supplement or drive human decision making, but in very different contexts (Hengstler et al. 2016). Chatbots are mainly implemented in different types of customers' services, such as healthcare (Hengstler et al. 2016), banking industry (Manser Payne et al. 2021), tourism and airlines (Meyer-Waarden et al. 2020). Autonomous cars are going to be used in the driving environment. Despite some examples of fully autonomous cars already exists, such as the robot-taxi in Arizona (Hecht 2018), their applications in urban and non-urban environment are still being discussed (Eggers and Eggers 2021; Hengstler et al. 2016). Finally both of the applications requires user involvement (Hengstler et al. 2016), but the nature and the level of interactivity differ (Du and Xie 2020). In particular, as chatbots aims to provide human-like interactions, they are generally characterized by anthropomorphized interfaces (Go and Sundar 2019). With regard to autonomous vehicles, despite they can be embedded with voice-assistants presenting a more or less anthropomorphized interface and conducting verbal interactions (Waytz et al. 2014), they generally prioritize unimodal (i.e. visual, auditory, or haptic) or multimodal (i.e. visual, auditory and haptic) signals (Salminen et al. 2019).

Thus, focusing on chatbots and autonomous vehicles allow us to investigate consumers' perceptions of two of the main discussed AI applications, taking into account different aspects of AI technology: verbal interactions and communication in the case of chatbots and usage in critical situations such as driving in the case of autonomous cars.

3. Research Problem

3.1. Artificial Intelligence from a Marketing Perspective

Considering the rapid development of new AI applications recently introduced in the market, the academic interest towards AI has started to increase in all research domains: from philosophy (Copeland 2015) to psychology (Collins and Smith 2013; Spiro et al. 2017), from medical science (Topol 2019) to agriculture (Jha et al. 2019) till management science and marketing (Kolbjørnsrud et al. 2016; Raisch and Krakowski 2021). In this regard, despite for many years marketing researchers and practitioners gave little attention to AI (Feng et al. 2020), during the last few years there has been a sharp increase of the number of publications concerning AI in peer-reviewed marketing journals, as we show in Chapter 1. Thus, as Vlačić (2021) suggests, the increasing success of AI in marketing practices is also reflected in research, with several significant contributions recently appearing particularly from 2017 onwards.

To face the increasing potential of AI applications to improve marketing strategies, researchers of the field have started to investigate different area and aspects of the technological evolution: from the applications of intelligent technologies (Marinova et al. 2017), to the improved services settings where the relationship with the client is facilitated by AI-based agents such as chatbots (Rust and Huang 2012; Wirtz and Zeithaml 2018); till investigations of AI-powered robotics (Wirtz et al. 2018) and explorations of AI-led marketing and sales strategies (Davenport et al. 2020). Despite this extensive list, marketing researchers still lack a cohesive understanding of how AI technologies have been applied and how consumers are using and interacting with them (Kaplan and Haenlein 2019; Mustak et al. 2021; Paschen et al. 2019). As Mustak and colleagues (2021) suggest synthesizing the literature on the use of AI in marketing can be useful to define the actual state of the art of the discipline and suggest a concrete path for future-focused academic research. In this regard, an objective analysis is crucial to evaluate the extant knowledge and identify knowledge gaps (Huang and Rust 2018; Russell and Norvig 2016). In addition, the academic community in the marketing domain has recently highlighted the need to define a stronger generalized theoretical framework and empirical research concerning artificial intelligence and its applications (Davenport et al. 2020; De Bruyn et al. 2020; Huang and Rust 2021a, 2021b, 2021c; Vlačić 2021). To respond to these needs, the first research question aims to better comprehend the academic landscape at the crossroad between marketing and AI:

RQ: 1) What is the state of art about artificial intelligence in the marketing literature, in terms of leading research streams and future research directions?

3.2. Consumers' Interactions with Conversational Agents

As mentioned above, conversational agents are one of the most well established technologies, which have been increasingly implemented in marketing operations. For this reason, the academic interest around conversational agents has seen a sharp increase during the last recent years. Customer service is one of the main areas where conversational bots, and in particular chatbot, are implemented (Huang and Rust 2018, 2021a; Rust and Huang 2012). Organizations make use of chatbot in customer service to cut costs and increase time efficiency. However, the potential benefits and costs related to the implementation of this technology are still being investigated. For instance, many studies have tried to comprehend which is the most effective and beneficial way to implement these technologies in order to guarantee a positive customer experience (Luo et al. 2019; Murtarelli et al. 2021; Sidaoui et al. 2020). In an article that we published in *the Journal of Service Management Research,* entitled "How Service Quality Influences Customer Acceptance and Usage of Chatbots?" Meyer-Waarden et al. (2020) have investigated the most relevant factors that drive chatbot acceptance and the intention to reuse it by integrating traditional and well-established theoretical frameworks, namely the SERVQUAL (Parasuraman et al. 2002) and the Technology Acceptance Model (Meyer-Waarden et al. 2020; Davis 1989). On the one hand, we demonstrate the importance of instrumental qualities of a chatbot such as ease of use and usefulness (Davis 1989; Kulviwat et al. 2007; Meyer-Waarden et al. 2020; Venkatesh 2000; Venkatesh et al. 2012). On the other hand, non-instrumental qualities, which concern the visual aesthetics and attractiveness of the chatbot, have a significant impact on its adoption (Meyer-Waarden et al, 2020). Our study also shows that the strongest determinant of the perceived usefulness of the chatbot is the agent's reliability. In the context of customer service through a chatbot, consumers expect a service to be performed accurately and in a timely manner. Chatbots should thus be designed to provide customers with relevant, reliable and functional content about the service, thus enhancing the customer's ability to use the firm's services. However, this is not always the case. In fact, research suggests that flawless operation (i.e., error-free service delivery) may prove utopian, above all in case of chatbots (Belanche et al. 2020). In this regard, chatbots often fail to properly work, causing negative feelings which might decrease consumers' perceived quality of life and satisfaction (Choi et al. 2021). However, despite service failure and customers' emotional responses such as anger and frustration have been a topic of particular interest in previous work on service technology (Choi and Mattila 2008), there is still a lack of research on AI-based service agents in service failure contexts (Belanche et al. 2020; Choi et al. 2021). Nevertheless, this topic of investigation is fundamental considering the high failure rate of chatbots currently implemented in customer services, which can have potential negative implications on consumers' wellbeing due to higher negative emotions. This problematic leads us to define the second research question:

RQ: 2) How consumers cognitively and emotionally respond when interacting with an AI-based conversational agent in the context of service failure?

3.3. Consumers Usage of Autonomous Vehicles

When investigating consumers' behaviors related to AI, it is important to consider the wide spectrum of AI applications and techniques that are being developed. If on the one hand chatbots represents a technology that is already present in the market, being an opportunity to investigate verbal interactions with AI; on the other hand, the future of autonomous vehicles (AVs) is surrounded by higher levels of uncertainty (Khastgir et al. 2018). The concept of vehicle automation refers to the replacement of some or all of the human labour of driving by electronic and/or mechanical devices (Faisal et al. 2019; Shladover 2018). In this regard, there are six levels of automation, from level 0 where a fully engaged driver is required at all times, to level 5 where an automated vehicle operates without the human driver (SAE International 2016). In order to control the driving task, AVs use artificial intelligence techinques such as neural netwoks and computer vision (Eggers and Eggers 2021). Despite the rapid technological advancement, we still do not know how consumers are going to use such a disruptive technology, in particular fully autonomous cars of level 5 (Eggers and Eggers 2021; Hohenberger et al. 2017). For this reason, autonomous driving and autonomous vehicles are currently among the most intensively researched and publicly followed technologies in the transportation and technological domain (Hengstler et al. 2016). Also the marketing field has started to be interested in the topic (Bertrandias et al. 2021; Eggers and Eggers 2021; Grewal et al. 2020; Hengstler et al. 2016; Huang and Qian 2021; Novak 2020). In this regard, even if the technology is still not mature, overcoming the technological barrier is not the only necessary step to do for autonomous vehicles to enter the market. Consumers need to trust fully autonomous cars in order to use them and research is required to understand the mechanism beyond trust and acceptance. Investigating trust is fundamental to foster trust calibration, avoiding situations in which individual ‘‘over-trust” or ‘‘under-trust” the car, which may be problematic in terms of safety. In fact, overly trusting the car might result in automation misuse, for instance, decreasing attention and concentration even if assistance technology is not able yet to deal with complex traffic situations (König and Numayr 2017; Lee and See 2004). However, not trusting the product enough may lead instead to automation disuse. For instance, not using the functions of the assistance system at level two such as speed control or automated braking could cause accidents that could be avoided. In this regard, investigating autonomous cars is also fundamental to comprehend their potential to increase well-being and quality of life by improving traffic conditions and life expectancies (Kaur and Rampersad 2018).

Besides trust and well-being, it is important to comprehend the factors that drive adoption of AVs. To use the functions, consumers need to form and shape positive beliefs surrounding the utility of adopting a such disruptive technology (Choi and Ji 2015; Huang and Qian 2021). However, if on the one hand many studies have already focused on trust and acceptance of fully autonomous cars (Eggers and Eggers 2021; Huang and Qian 2021), on the other hand, there is still a lack of understanding on how the experience with different functions and levels of automation is going to shape consumers perceptions of the technology (Rödel et al. 2014). In fact, autonomous vehicles are going to be gradually introduced in the market, thus giving consumers the time to experience the different levels of automation, familiarizing with the functions and gradually forming their beliefs and trust (Hartwich et al. 2018). Thus, taking into account the different development stages of a technology that is still not mature, adopting a dynamic research approach, can be helpful to grasp the real formation and transformation of consumers' beliefs after different experiences with the new technological product. In this context, autonomous cars offer an ideal research opportunity to investigate consumers' perceptions of an intelligent technology that is still being developed and transforming. However, still few researchers have investigated autonomous vehicles taking into account their different automation levels (Rödel et al., 2014). This research gap inspires our third research question:

RQ:3) How consumers' trust, well-being and usage intentions of AI based products (e.g. fully autonomous vehicles) evolve when experiencing different levels of automation?

3.4. On the Ethics of AI

The possibility of creating machines able to learn from data and make critical decisions in important situations raises many ethical issues which are at the centre of the debate of businesses, universities and institutions (Bonnefon et al. 2016; Bostrom and Yudkowsky 2011; Novak 2020). In this regard, on an institutional level, governments have started to define principles to guide the ethical development of AI. In 2019, the High-Level Expert Group on AI of the European Commission presented the "Ethics Guidelines for Trustworthy Artificial Intelligence" (European Commission 2019). Their Guidelines propose a set of 7 key requirements that AI systems should meet in order to be considered as trustworthy: human agency and autonomy; technical robustness and safety; privacy and data governance; transparency; diversity; societal and environmental well-being; accountability (European Commission 2019).

In addition, researchers in the business and the marketing domains have started to face the inevitable ethical discussion that AI raises, trying to comprehend and defining the ethical issues and potential solutions behind the introduction of AI in business and society. In this context, many are the ethical issues that researchers emphasize. For instance, AI applications and systems can be discriminatory and subjected to biases (Du and Xie 2020; Hermann 2021). Discrimination can be due to customer prioritization based on demographic and economic factors (e.g. Libai et al. 2020), targeting (e.g. Matz and Netzer 2017) or focusing on vulnerable consumer groups (e.g. Puntoni et al. 2021). Other researchers raise the ethical issues related to consumers' privacy and data governance (Cloarec 2020; Du and Xie 2020; Kumar et al. 2021; Thomaz et al. 2020). In this regard, as AI algorithms are able to access and exploit huge amounts of consumers' data, it is important to comprehend the boundaries and the trade-off between the benefits of AI applications such as personalization and the costs, in particular the lack of control over the personal information (Cloarec 2020). Other researchers also highlight the need to increase the transparency of algorithms (Huang and Rust 2021a; Rai

2020). In fact, as AI algorithms are increasingly able to make decisions which can affect consumers on various levels, it is important to comprehend the criteria beyond their decision making process. In this regard, the more complex and evolved AI becomes, the more consumers choice, autonomy, and well-being might be undermined (André et al. 2018). Also, higher levels of intelligence are associated with higher risks of unemployment due to job replacement (Du and Xie 2020). However, researchers also highlight the strong potential of AI of augmenting rather that replacing humans (Henkel et al. 2020; Raisch and Krakowski 2021).

Despite the recent new contributions which aim to shed light on the ethical dilemma that AI raises, to date the topic of AI ethics in the marketing discipline is rather fragmented (Hermann 2021). In fact, researchers often focus on investigating specific principles and specific applications (Hermann 2021). In addition, the discussion of ethical issues of AI in marketing is partly anecdotal and consumers concerns about AI ethics have not been extensively investigated (Davenport 2021; Herman 2021). However, understanding consumers ethical concerns might be fundamental to comprehend how trust towards the technology and the intention to use it are developed (Argandoña, 1999). To overcome this research gap, we define the follow research question:

RQ:4) How consumers' ethical concerns about AI-based products vary and affect trust and intention to use the AI technology?

4. Contribution to Theory

Through our research, we aim to comprehend how consumers use and interact with intelligent technologies, in particular focusing on two current applications: autonomous cars and chatbots. Investigating these two different products allows us to take into account the complexity of the technology and part of the wide spectrum of the existing AI techniques.

Before empirically investigating AI-based applications, we present in Chapter 1 an in-depth analysis of the existing literature where we identify and define the research questions that drives our research concerning: 1) consumers' cognitive and emotional reactions when interacting with technologies that are able to simulate human-like conversations; 2) factors affecting consumers'intention to use AI-based technologies such as fully autonomous vehicles and their evolution across levels of automation; 3) consumers ethical concerns towards AI products and their effect on trust and usage intentions. By studying these issues and answering our research questions, this research contributes to the theory in the following manners.

In Chapter 1, we firstly describe the state of the art of the emerging marketing literature around the topic. We show the growing interest of the academic community who has recently started to deeply investigate AI, mirroring also the increased societal and institutional interest on the topic. In particular, we conduct for the first time a hybrid literature review through scientometric and the Theory–Context–Characteristics–Methodology (TCCM) protocol (Paul and Rosado-Serrano 2019; Rosado-Serrano et al. 2018). This mixed approach allows us to investigate the literature at both the macro and micro level. In this regard, we first provide a global overview of the academic landscape on the topic through the scientometric approach, identifying seven main streams of research (macro-level analysis). Next, we adopt a systematic approach investigating in detail each stream of research (micro-level analysis), by classifying the main theories, the methodologies, the industries, the variables used in each stream of research. Building upon these findings, we identify new questions that aim to drive research towards a better understanding of the evolving field of AI in marketing. Thus, we contribute to the literature by providing foundation of knowledge on the topic, identifying areas of prior scholarship and gaps in research that justify the need for future investigations.

In the second part of the thesis, which includes Chapter 2 and Chapter 3, we empirically investigate consumers' interaction and usage of two current AI applications. Each application allows us to take into account different aspect of the technology.

In Chapter 2, we investigate human interactions with conversational agents in service failure contexts, focusing on the emotional components of the interaction mainly applying Cognitive Appraisal Theory of Emotion (Roseman 1991), Attribution Theory (Weiner 2000) and Anthropomorphism Theory (Aggarwal and McGill 2007). Thus, we contribute to the emerging literature of AI-based service and to consumer behavior theories showing how according to the type of interaction, with a human service agent or a chatbot, on the one hand customers differently experience emotions in failing AI-based service settings; on the other hand, they tend to adopt similar coping strategies to regulate their emotional responses (Davenport et al. 2020; Huang and Rust 2018; Meyer-Waarden et al. 2020; Wirtz et al. 2018). In particular, we contribute to the CASA Theory (computers as social actors; Nass and Moon 2000) better comprehending human-technology and AI-based chatbot interactions, suggesting that customers tend to adopt confrontive coping strategies even when interacting with an AI based chatbot, thus applying social rules also in case of negative situations. In addition, we show the determinants of such irrational behaviors, namely perceptions of intentions and ability (Kervyin et al. 2012). Finally, we contribute to Attribution Theory (Weiner 2000) by shedding light on how attributions of responsibility toward service agents and firms change depending on the identity of the service providers, namely humans compared to AI based chatbot agents, and the anthropomorphic visual cues (Aggarwal and McGill 2007; Araujo 2018; Blut et al. 2021; Epley et al. 2018; Go and Sundar 2019; Lee 2010).

In Chapter 3 we focus on a different AI-based product, namely autonomous cars. We enrich the existing literature by taking into account the complexity of the technology across its development stages. As Huang and Qian (2021) suggest, differentiating between the different automation levels can help to better understand the potential drivers of acceptance. Thus, we also address the need to investigate how gradually experiencing different levels of automation affect consumers' beliefs around complex disruptive AI technologies (Huang and Quian 2021). Showing that investigating consumers' perceptions at the different development stages can help the understanding of trust, well-being and behavioral intentions towards fully autonomous cars, we suggest that such «dynamic » approaches can generate more in-depth insights compared to dominant « static » approaches focusing only on one level of automation.

Secondly, we contribute to the literature on technology adoption by integrating the traditional UTAUT framework with psychological Theory of Subjective Well-being (Diener 1999; Diener and Chan 2011) and Trust in Technology (McKnight et al. 2011). If the well-established UTAUT Framework helps us to identify the cognitive antecedents of adoption, the Well-being and Trust Frameworks shed light on the psychological mechanisms behind adoption. As the main goal of technological innovation should be to improve consumers' quality of life, increasing comfort and safety, investigating subjective well-being is becoming urgent to comprehend how AI technology can effectively improve it (Bertrandias et al. 2021). In addition, we highlight the link between trust and well-being. In fact, investigating trust is fundamental as both ''over-trust" as well as ''under-trust" may be problematic for consumers' well-being, putting their life in danger thus decreasing the perceived quality of life (König and Neumayr 2017; Lee and See 2004).

Finally, in Chapter 4 we contribute to the growing marketing literature on AI ethics shedding light on consumers 'ethical perceptions of different AI products (Du and Xie 2020; Murtarelli et al. 2021). In particular, we show that when discussing ethical concerns and trust towards AI, researchers should take into account the wide spectrum of AI techniques and the different product characteristics. In fact, according to the different product innercharacteristics, different ethical concerns and different components of trust emerge. Thus, we also contribute to the literature on trust towards AI in two ways (Glikson and Woolley 2020). First, we highlight the link between ethics and trust, which is fundamental to drive acceptance of these new disruptive technologies (Argandoña 1999). Second, we show that according to the type of technology, emotional or cognitive components of trust might be more prominent (Glikson and Woolley 2020). When discussing chatbots, for instance, emotional trust might play a key role, as individuals highlight the importance of the emotional design of the machine and the need of developing individualized relationships. When discussing autonomous vehicles, cognitive aspect of trust related to the beliefs of safety and reliability of the technology emerge.

To conclude, the innovative mixed-method methodology applied in the study offer new insights on the topic, providing explorative empirical evidence of consumers' ethical concerns. Since many studies on AI ethics are mainly conceptual (Bostrom and Yudkowsky 2011; Du and Xie 2020b; Jobin et al. 2019; Murtarelli et al. 2021), we respond to the need of conducting more empirical research by adopting a pragmatic approach and investigating ethics from the consumers' point of view.

5. Contribution to Methods

On a methodological level, we offer numerous contributions that advance knowledge about the mixed methods research, the research tools and applications that can be used in the academic field. In particular, in Chapter 1 we adopt a mixed approach combining for the first time two innovative methods for conducting the literature review: scientometric (van Eck and Waltman 2010) and the Theory-Context-Characteristics-Methodology framework (Paul and Rosado-Serrano 2019; Rosado-Serrano et al. 2018). Combining these two methodological approaches offers an opportunity to investigate the literature at both the macro-level and micro-level. In fact, thorugh the scientometric approach we firstly describe the scientific landscape, the evolution of the field and we identify the main research streams. The TCCM approach, instead, allows us to investigate in detail each article focusing on the main theories, the constructs, the contexts and the methodologies applied, thus giving a detailed description of the field (Paul and Rosado-Serrano 2019; Rosado-Serrano et al. 2018).

Besides, as our studies are mainly experimental, the methodological contributions of the thesis involve the implementation and usage of numerous innovative tools and applications, which increase the reality and credibility of the experiments. In particular, in Chapter 3 we simulate a realistic interaction with an AI-based chatbot by designing an interactive video instead of using traditional written scenarios. This approach allows creating more credible scenarios, helping the participants of the study to better project themselves in the situations investigated. Also in Chapter 3, we integrate field and simulator studies to investigate consumers' responses to increased levels of automation of autonomous vehicles. In particular, in Study 3, we use a real level 2 semi-autonomous car (Mercedez-Benz EQC) to test consumers' responses to the semi-autonomous functions. In Study 4, we implement a simulator able to reproduce a realistic driving environment to test a level 5 fully autonomous car. This combined approach allows us to overcome the limitations of traditional, static and abstract surveys, offering a direct experience with the disruptive technological product, having a real understanding of users' behaviors when trying and using the technology (Kempf 1999; Smith 1993). In addition, thanks to the implementation of a within-subject design that integrates the field and simulator studies, we design a new dynamic approach that has the advantage to test consumers' interactions with increased levels of automation, exploring a technology that is still not present in the market.

Finally, we also offer a methodological contribution in Chapter 4, where we combine both qualitative and quantitative approaches implementing topic modelling and structural equation modeling (SEM). On the one hand, topic modeling is an innovative AI-based approach used to identify latent structures in a text body for insights generation (Berger et al. 2020; Humphreys and Wang 2018). This approach is particularly indicated when investigating a new topic. On the other hand, SEM is a well-established statistical modeling method used to investigate relationships among observed and latent constructs, which allows us to test the effect of the new topics on well-established variables.

6. Contribution to Practice

Our research offers numerous insights to managers and practitioners who want to implement AI technologies in two different contexts. In particular, in the context of customer service management, we offer insights to managers who want to implement conversational agents, and in particular, chatbots, to handle complex failures such as in double deviation. If on the one hand there is already anecdotal evidence that consumers might negatively perceive the automated service management, we offer empirical evidence that implementing such technologies in complex situations can have negative repercussions for the firm. In fact, our studies suggest that in the same failing situation, customers tend to attribute more responsibility for the service failure to the firm when they interact with a chatbot rather than a human agent. In turn, their anger and frustration, manifested in confrontive coping strategies, predominantly target the firm. However, we offer a solution that might help mitigate the negative attributions to the firm. In particular, we suggest that anthropomorphizing the chatbot with human-like visual cues, in particular a face and a name, could reduce attribution of responsibility to the organization and promote both problem-focused and emotion-focused coping strategies. The first one can be useful to handle the service failure in a more rational way, looking for solutions instead than giving up and abandoning. The second one might help consumers to cope with the negative emotions caused by the negative event by restoring the emotional balance disrupted by the event. Thus, we suggest that creating a sense of human connection, so that consumers believe they are in the presence of another social entity (van Doorn et al. 2017), may help mitigate negative attributions and help consumers to deal with the situation.

Our studies also show that consumers might experience strong negative emotions when interacting with an AI-based chatbot. Therefore, we suggest that companies need to find a way to actively deal with customers' negative emotional reactions. However, if on the one hand it might seem that implementing “emotional” chatbots which are able to simulate emotion and empathy could be an optimal solution; on the other hand, results of the study discussed in Chapter 4 suggest that managers should carefully balance chatbots’ emotional reactions which may be perceived as unethical because lacking of authenticity. In fact, chatbots are still at the mechanical and analytical level of artificial intelligence, not having intuition and empathy (Huang and Rust 2018) and not being enough developed to truly understand consumers’ emotions and answer adequately. Thus, we suggest that when interacting with chatbots, efficiency may be preferred to unreal and inappropriate emotional reactions of the chatbot. However, when emotions are involved, we suggest that companies need to find the optimal balance between “tech” and “touch” in service encounters (Giebelhausen et al. 2014). In complex situations, service managers should assign human agents to deal with complex negative emotional reactions and to create meaningful relationship with consumers. In this regard, Chapter 4 suggests that when implementing chatbots, managers should give particular attention to the consumer-bot relationship. In fact, as bots fail to comprehend and address consumers ‘individual needs, the relationships with consumers might suffer. Despite chatbots can benefit the company by offering more efficient services, the lack of adaptability can harm the firm being detrimental for developing long-term and trustful relationships with consumers.

If on the one hand when talking about chatbots the emotional and interactional component of the technology emerge, on the other hand, when talking about autonomous vehicles, the cognitive beliefs related to the reliability and safety of the technology seem to be predominant. Thus, technologies that involve decision making in critical situations such as autonomous cars raise other type of concerns and perceptions. In this regard, in Chapter 3, we investigate consumers' perceptions towards autonomous cars, highlighting the importance of trial and experience with level 2 and level 5 of automation to increase consumers' trusting beliefs towards fully autonomous cars and behavioral intention to use the technology. The more consumers experience increasing levels of automation, the more they might get confident about the autonomous cars 'abilities to drive effectively and properly (McKnight 2011). In addition, the level of ambiguity around autonomous technology and algorithms, which makes them appear unpredictable and untrustworthy in many scenarios, can be overcome through higher experience with functions with higher levels of autonomy. In this regard, as suggested in Chapter 4, company needs to be transparent around the way algorithms are implemented and make decisions. Consumers need to be informed about the rules behind algorithmic decision-making and on how their data are processed. In order to increase trust, the ethical design behind algorithmic decision-making should follow clear and standardized regulations. Addressing consumers' ethical concerns is important as it may help to increase trust over the technology.

In addition, we suggest that also the perceived well-being is an important driver of adoption of autonomous technologies. However, the way fully autonomous functions increase well-being is still not clear in consumers 'mind. For this reason, we suggest that managers should clarify how adopting higher levels of automation could benefit consumers in term of increased quality of life, perceived well-being and positive feelings.

7. Dissertation Overview

The thesis includes three main parts with fourth chapters (Figure 1). In the first part of the thesis, the first chapter presents a hybrid literature review with scientometric and TCCM protocol of 167 peer-reviewed papers on artificial intelligence in marketing and consumers behaviors. Here we define the research questions of the next chapters, and we propose a research agenda for future research. The second part of the thesis includes the second and third chapters, with the investigations of two practical AI applications: chatbots (chapter 2) and autonomous cars (chapter 3). The third part focuses on the ethics of AI. In particular, in chapter 4 we present two investigations on consumers 'ethical concerns towards chatbots and autonomous vehicles. Finally, we present the conclusion, where we discuss the theoretical and methodological contributions, the managerial implications, the implications for policymakers, the limitations of our research and the future research direction.

Figure 1 Overview of the thesis

INTRODUCTION

PART I: Defining AI in Marketing

Chapter 1
Artificial Intelligence in Marketing Research:
Scientometric, TCCM Review and a Research Agenda

PART II: Practical AI Applications

Chapter 2
Rage Against the Machine:
Experimental Insights into Customers' Emotional Responses, Attributions of Responsibility and Coping Strategies in AI-Based Service Failure

Conferences:
Pavone, G., Meyer-Waarden, L., Munzel, A. (2020). When technology fails: rage against the machine or self-control? Investigating consumers'negative emotions in AI-based service failure scenario. **Association for Consumer Research,** Working paper, 1-4 October 2020.
Pavone, G., Meyer-Waarden, L., Munzel, A. (2021) When technology fails: rage against the machine or self control? Investigating consumers'negative emotions, sense of power and coping strategies in AI-service failure scenarios. **36 ème Congrès International de l'Association Française du Marketing (AFM), 2021**, 19-21 May 2021.
Pavone, G., Meyer-Waarden, L., Munzel, A. (2021) When technology fails: rage against the machine or self control? Investigating consumers'negative emotions, sense of power and coping strategies in AI-service failure scenarios **49th European Marketing Academy Annual Conference (EMAC) 2021**, 26-28 May 2021.

Chapter 3
Now, Take Your Hands From The Steering Wheel!
How Trust, Well-being and Privacy Concerns Influence Intention to Use
Semi- and Fully Autonomous Cars

PART III: On the Ethics of AI

Chapter 4
Consumers' Perspectives on AI Ethics and Trust:
an Explorative Investigation of Ethical Concerns Towards Autonomous Cars and Chatbots

Conferences:
Pavone, G. (2021) Consumers' perspectives on AI ethics and trust: an investigation of ethical concerns towards autonomous cars and chatbots. **36ème Congrès International de l'Association Française du Marketing (AFM) 2021**, 19-21 May 2021.
Pavone, G. (2021) Consumers' perspectives on AI ethics and trust: an investigation of ethical concerns towards autonomous cars and chatbots. **49th European Marketing Academy Annual Conference (EMAC) 2021**, 26-28 May 2021.
Pavone, G. (2021) Consumers' perspectives on AI ethics and trust: an explorative investigation of ethical concerns towards autonomous cars and chatbots. **Association for Consumer Research,** Working Paper, 28-30 October 2021.

OVERALL THEORETICAL, METHODOLOGICAL, MANAGERIAL CONTRIBUTIONS, RESEARCH LIMITS AND FUTURE RESEARCH DIRECTIONS

7.1. Chapter 1 – Abstract

Considering the increasing numbers of publications in the last recent years, there is an urgent need to comprehend how the marketing field related to AI is evolving (Mustak et al. 2021; Vlačić 2021). In this context, this literature review explores the following research questions: (1) how does the marketing literature synthesize artificial intelligence in marketing? (2) What are the leading research streams? (3) What are the future research directions? We draw from Paul and Criado (2020) and Vlačić (2021) conducting a hybrid literature review (Paul and Criado 2020). First, we select 167 peer-reviewed papers published in the marketing field concerning artificial intelligence in marketing and consumer behaviors. Second, we conduct a bibliometric and scientometric review to understand the evolution of the field. Next, drawing from keywords co-occurrence analysis we identify seven research clusters, each of them discussing different research topics: AI techniques and applications; consumers-AI interactions in service settings; ethics of AI; AI, company transformation and digitalization; consumers' behaviors and psychology in the era of AI; AI and social media management; AI, financial services and e-commerce. We review each cluster following the TCCM protocol (Paul and Rosado-Serrano 2019; Rosado-Serrano et al. 2018) shedding light on both theoretical and empirical aspects of the specific research domain (Chen et al. 2021). Finally, we propose a research agenda to guide the scientific community towards new avenues of research at the crossroad between marketing and AI.

7.2. Chapter 2 – Abstract

In their interactions with chatbots consumers often encounter technology failures that evoke negative emotions. To clarify the effects of such encounters, this article addresses how service failures involving artificial intelligence (AI)–based chatbots affect customers' emotions, attributions of responsibility and coping strategies. In addition to comparing the outcomes of a service failure involving a human agent versus a chatbot (Study 1, N=122), the research framework integrates the potential influences of anthropomorphic visual cues and intentionality (Study 2, N=120 and Study 3, N=120). Applying three experimental designs, the study reveals that when interacting with chatbots, customers blame the company more for the negative outcome, experiencing higher frustration. We show that because the chatbot has no sense of purpose and control over its actions, it is not seen as responsible for the outcome. However, we suggest that anthropomorphic visual cues might help to mitigate the negative attributions to the company. The more the chatbot resembles a human and is perceived as having intentions and the ability to implement them, the more consumers employ problem-focused strategies, engaging in confrontive coping, venting their emotions to the chatbot and looking for solutions. Individuals also tend to use emotion-focused strategies and control their emotions to cope with the negative situation, regardless of the anthropomorphic visual cues.

7.3. Chapter 3 – Abstract

In the last decades, the focus on the development of Autonomous Vehicles (AVs) has increased due to its many promised benefits like increased consumers' well-being through improved safety, traffic efficiency and reduced emissions (Khastgir et al. 2018). In this regard, manufacturers have already started to equip new vehicles with semi-sophisticated autonomous functions that might help to increase trust and acceptance of fully autonomous cars. In this context, we integrate the well-established UTAUT framework (Venkatesh et al. 2003, 2011) with Trust Theory (Mcknight 2005; Mcknight et al. 2011), Privacy Calculus Theory (Dinev and Hart, 2006) and Theory of Subjective Well-being (Diener 1999; Diener and Chan 2011), conducting four studies: 1) an online survey on fully autonomous cars to test our model with a representative sample (N=331); 2) a replication study with a convenience sample (N=138); 3) a field study with a semi-autonomous car of level 2 (N=138); 4) a simulator study with a level 5 fully autonomous car (N=138). By implementing a within-subject design, we are able to investigate the evolution of consumers' perceptions of fully autonomous cars across the levels of automation. Results suggest that individuals might still not be ready to adopt level 5, not perceiving its increased benefits in terms of well-being, helpfulness and effort expectancy. However, experiencing the functions might play a fundamental role in clarifying how they can positively affect consumers' quality of life, increasing the ease of use related to the technology, the trusting beliefs of helpfulness and reliability, and decreasing the privacy concerns related to the technology. In addition, the more individuals experience the technology, the more they trust it to have the ability to deliver the functionalities promised, increasing the behavioral intention to use it.

7.4. Chapter 4 – Abstract

This paper investigates consumers' ethical concerns, trust and usage intention of intelligent products employing a mixed methods approach. First, we get insights about consumers' ethical concerns towards autonomous cars (N=138) and chatbots (N=161) using topic modeling. Second, we predict their effect on trust and usage intention through structural equation modeling. Results show that ethical concerns differ when using and interacting with products which present different levels of intelligence and interactivity. In particular, ethical concerns about chatbots emphasize the interactivity of the machine, involving human replacement, the machine's emotional design, the need of having adapted, personalized interactions and the privacy concerns as critical issues. Ethical concerns about autonomous cars highlight instead the complexity of the technology in terms of intelligence and decision-making capacity, involving the transparency of algorithmic decision-making, the ethical design, road safety and accessibility. We find an opposite perception of adaptability versus standardisation of algorithms in chatbots and autonomous cars: to increase trust, chatbots, perceived as unethical because unable to truly understand individual needs and emotions following predetermined rules, should guarantee personalized, unique interactions, being able to adapt and offer an authentic experience; autonomous cars, perceived as unethical if their algorithms are not standardized, should follow common, transparent rules. The study also suggests that different components of trust emerge according to the AI-based product: when discussing chatbots, the emotional component of trust seems to be predominant; when discussing autonomous vehicles, instead, cognitive beliefs emerge.

8. Declaration of Contributions

Chapter 1: This chapter is entirely written by the author. The methodological approach was discussed with Pr. Lars Meyer-Waarden (Université Toulouse 1 Capitole) and Pr. Andreas Munzel (Université Toulouse 1 Capitole).

Chapter 2: This chapter is joint work with Pr. Lars Meyer-Waarden (Université Toulouse 1 Capitole) and Pr. Andreas Munzel (Université Toulouse 1 Capitole). The co-authors funded the data collection of the questionnaires of Study 2 and Study 3 to two representative pools of French and US consumers. The author conducted most of the work for this chapter.

Chapter 3: This chapter is joint work with Pr. Lars Meyer-Waarden (Université Toulouse 1 Capitole), Pr. Andreas Munzel (Université Toulouse 1 Capitole), Pr. Marc Kuhn (DHBW Stuttgart) and Dr. Julien Cloarec (Univesité de Lyon). The questionnaire of Study 1 was funded by Pr. Lars Meyer-Waarden and Pr. Andreas Munzel. The research materials used in Studies 2, 3 and 4 were funded and provided by Pr. Marc Kuhn. The data collection was conducted by the author during the research visiting at DHBW. The statistical analysis was conducted by Dr. Julien Cloarec. The author conducted most of the work with the exception of the statistical analysis.

Chapter 4: This chapter is independently and solely written by the author.

Introduction

PART I
Defining AI in Marketing

Chapter 1. Artificial Intelligence in Marketing Research: Scientometric, TCCM Review and a Research Agenda

PART II
Practical AI Applications

Chapter 2. Rage Against the Machine: Investigating Consumers Negative Emotions, Attributions of Responsibility and Coping Strategies in AI-Based Service Failures

Chapter 3. Now, Take your Hands from the Steering Wheel! How Trust, Well-Being and Privacy Concerns Influence Intention to Use Semi- and Fully Autonomous Cars

PART III
On the Ethics of AI

Chapter 4. Consumers' Perspectives on AI Ethics and Trust: an Explorative Investigation of Ethical Concerns Towards Autonomous Cars and Chatbots

Overall Theoretical, Methodological, Managerial Contributions, Research Limits and Future Research Directions

PART I

DEFINING AI IN MARKETING

CHAPTER 1

ARTIFICIAL INTELLIGENCE IN MARKETING RESEARCH:

SCIENTOMETRIC, TCCM REVIEW AND A RESEARCH AGENDA

1. Introduction

Recently, the rapid evolution of artificial intelligence (AI)-based applications has attracted growing interest from the marketing community. In particular, many researchers have investigated different aspects of AI applications in the context of marketing, including the way AI is affecting the different phases of the marketing processes, such as analysis, segmentation, and positioning (Huang and Rust 2021b, 2021c); AI applications in service settings intended to improve the customer experience (Huang and Rust 2018; Wirtz et al. 2018); employee augmentation via AI applications (Huang and Rust 2021b; Sowa et al. 2021); and consumer adoption of AI technology (Fernandes and Oliveira 2021; Schmitt 2020). Considering the rapidly increasing number of related publications in recent years, there is an urgent need to understand how the marketing field is evolving in relation to AI (Mustak et al. 2021; Vlačić 2021). In this context, this literature review explores the following research questions: (1) How does the marketing literature synthesize AI in the context of marketing? (2) What are the leading research streams? (3) What are the future research directions?

To answer our research questions, we follow Paul and Criado (2020) and Vlačić (2021), conducting a hybrid literature review. After selecting 167 peer-reviewed papers published in the marketing field concerning AI in the context of marketing and consumer behavior, we conduct a scientometric review to analyze this extensive number of peer-reviewed papers by using statistical tools such as R and Visualization for Similarities (VoSviewer). In this phase, we first describe the evolution of the field and the scientific landscape in terms of journals and landmark publications in the marketing literature. Second, we identify research topics and co-occurrences of particular themes (Paul and Criado 2020). A co-occurrence analysis allows us to define the conceptual structure of this literature, categorizing it into clusters of articles according to the co-occurrence of keywords and research themes.

Next, we conduct an in-depth systematic review of the 167 selected and clustered papers to understand the emerging research themes. In particular, we employ the Theory–Context–Characteristics–Methodology (TCCM) review protocol (Paul and Rosado-Serrano 2019; Rosado-Serrano et al. 2018), which sheds light on both the theoretical and the empirical aspects of a specific research domain. Our in-depth review of the research papers selected for analysis also helps us identify relevant research gaps. Thus, we finally present a research agenda that guides the scientific community toward new avenues of research at the interface between marketing and AI.

2. Methodology

2.1. Phase 1: Data Collection

The data collection began by searching for articles that contained (in their title, abstract, or the authors' keywords) terms such as "marketing" or "consumer behavior" AND "artificial intelligence OR intelligent system(s), as recommended by Martínez-López and Casillas (2013). We selected one academic database, Scopus, to find articles linked to the topic. Many authors suggest that Scopus has broader coverage than other databases, including more than 20.000 peer-reviewed journals from different publishers (Fahimnia et al. 2015; Verma et al. 2021). Through this first search we find 2,430 documents. To ensure the validity of the review, we limited our analysis to ranked marketing academic journals that had a peer-review process (Podsakoff et al. 2005). Thus, we only selected articles published in ranked academic journals and written in English. We excluded book chapters, book reviews and conference proceedings (López-Duarte et al. 2016). In order to graphically depict the evolution of this research topic, we did not impose any time constraints. Thus, the final search criteria at the date of extraction (12/04/2021) resulted in 167 articles (Table 1).

Table 1 Description of the dataset

MAIN INFORMATION ABOUT DATA	
Timespan	1987:2021
Sources (Journals)	27
Documents	167
Average years from publication	2.47
Average citations per documents	13.01
Average citations per year per doc	4.221
References	12795
DOCUMENT TYPES	
Article	156
Editioral	1
Note	4
Review	6
DOCUMENT CONTENTS	
Keywords Plus (ID)	97
Author's Keywords (DE)	632
AUTHORS	
Authors	470
Authors Appearences	533
Authors of singe-authored documents	17
Authors of multi-authored documents	453
AUTHORS COLLABORATION	
Single-authored documents	19
Documents per Author	0.355
Authors per Document	2.81
Co-Authors per Documents	3.19
Collaboration Index	3.06

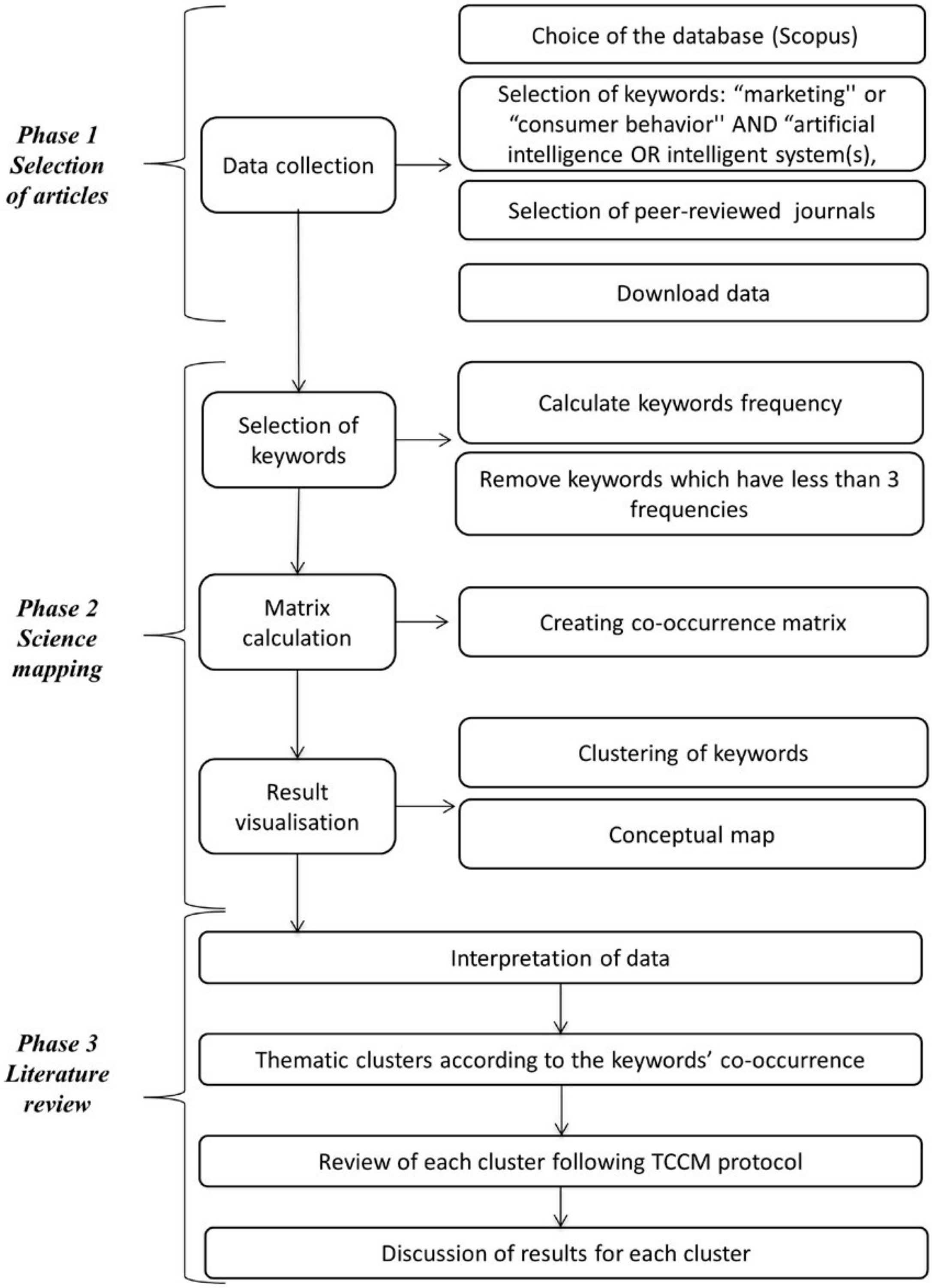
2.2. Phase 2: Bibliometric Data Analysis

After collecting the data, we conduct a bibliometric analysis. The steps of our procedure are shown in Figure 2. Bibliometric analyses are used for quantitative and qualitative academic research assessments (Verma and Yadav 2021). Specifically, according to Verma and Yadav (2001, p.114), “bibliometrics is a set of methods used to study or measure texts and information, especially in large datasets”. There are two main procedures used in bibliometric analyses: performance analysis and science mapping (van Raan 2005). Through performance analyses, researchers assess actors such as authors, journals, publishers and countries and their impacts on a given field (van Raan 2005; Verma and Yadav 2021). In contrast, the aim of science mapping is to show the structure and dynamics of a body of scientific research, offering a visual representation of the research field.

Thus, in the first step, we conduct a bibliometric analysis with the open-source R package "bibliometrix" (Aria and Cuccurullo 2017) to identify influential aspects of the examined literature, particularly in relation to the evolution of the field, key journals in the marketing field and key publications (performance analysis). Next, we adopt a science mapping procedure, identifying the research streams in this literature through a bibliometric co-occurrence analysis (Dzikowski 2018; Fetscherin 2010). Following Mustak et al. (2021), we use VOSviewer, a free Java application used for analyzing and visualizing citation and co-occurrence networks within scientific collections. VOSviewer is able to create clusters and construct bibliographic and conceptual maps based on a co-occurrence matrix. The construction of such a map is a process that consists of three steps (van Eck and Waltman 2010). In the first step, a similarity matrix is calculated based on a co-occurrence matrix of author keywords. According to Chen et al. (2010), networks based on keywords indicate the conceptual structure of a body of literature. In the second step, a map is constructed by applying the VOS mapping technique to the similarity matrix. Finally, in the third step, the map is translated, rotated, and reflected (van Eck and Waltman 2010).

Thus, after selecting and collecting the data from Scopus, we proceed with the co-occurrence analysis using VOSviewer. We use a full counting method, where each co-occurrence has the same weight. We select the minimum number of keyword occurrences; specifically, keywords with fewer than 3 co-occurrences are not included. Of the 632 total keywords, 44 meet the threshold. The total strength of the co-occurrence links between each keyword and the other keywords is calculated. Based on the co-occurrence links, each keyword is associated with a research theme. The higher the frequencies of a given co-occurrence between keywords, the closer the corresponding research themes are (Chen et al. 2016). Next, we proceed to use VOSviewer to calculate the matrix, visualizing the results through keyword clusters and a conceptual structural map according to the research themes. The last step of the process consists of interpreting the data, which is discussed in the next section.

Figure 2 Steps of the procedure (adapted and extended from Chen et al. 2016)



2.3. Phase 3: TCCM Protocol

Once we categorize the literature into thematic clusters according to the keyword co-occurrences, we give a title to each cluster (Mustak et al. 2021). Specifically, we conduct an in-depth review of the 167 papers to interpret their data and to describe and assign related articles to each cluster (Paul and Criado 2020). Thus, we present a synthesis of the literature on AI in the context of marketing, analyzing each paper in each cluster according to its keywords and object of analysis. In particular, following Paul and Rosado-Serrano (2019) and Rosado-Serrano et al. (2018), we conduct a Theory–Context–Characteristics–Methodology (TCCM) review protocol. Accordingly, we first review the theoretical frameworks that are most frequently used to explain each cluster (Chen et al. 2021). Then, adopting a more empirical perspective, we assess the different contexts, particularly, the industries and countries, in which this research was carried out (Chen et al. 2021). Next, we adopt a microperspective, investigating the various relevant concepts of each cluster. Specifically, we review the types of variables that are studied and we provide a differentiated analysis of the independent, mediating, moderating, or dependent variables. Then, we assess the key methodological aspects of the field, including the research approaches and data types that are used. In the last phase, we discuss each cluster according to the main research topics that emerge from it. This in-depth review allows us to identify the research themes that emerge from each cluster and determine how they are investigated. Finally, based on our analysis of each cluster, we define the relevant research gaps and propose a research agenda.

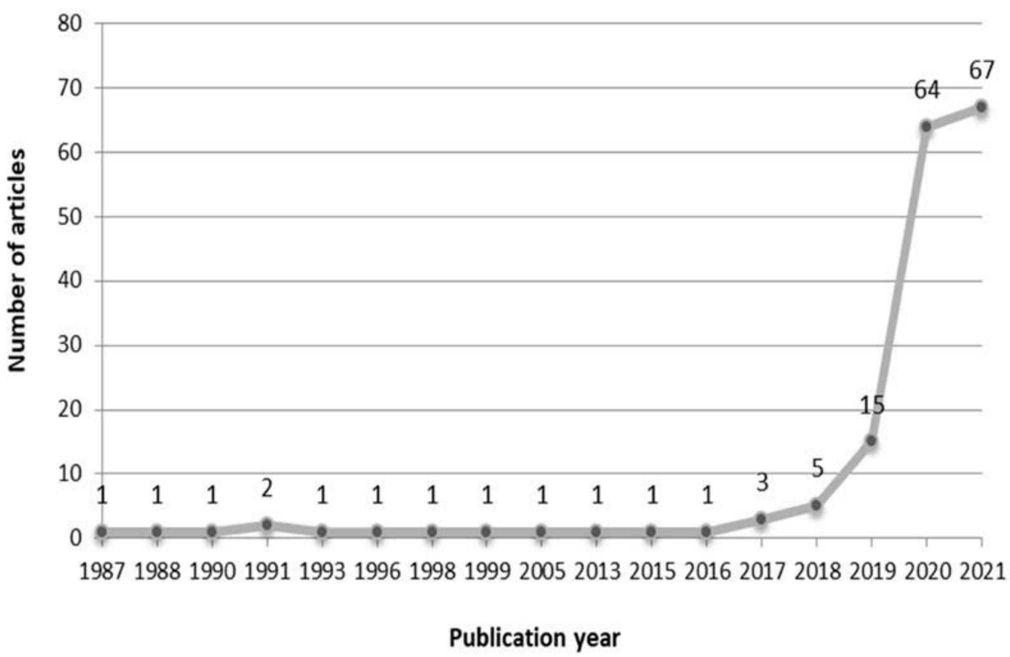
3. Results of the Scientometric Analysis

Using the R package "bibliometrix", we conduct a performance analysis investigating the evolution, landmark journals and publications of the examined field.

3.1. Performance Analysis Results

Scholars in the marketing community have been directing an increasing level of attention toward the field of AI. In this regard, Figure 3 shows the year wise distribution of the 167 articles selected, which were published between 1987 and 2021 in top-ranked academic marketing journals. We observe a slight increase in publications starting in 2017, which sharply increases in 2020, indicating the strong recent interest of the academic community in the topic.

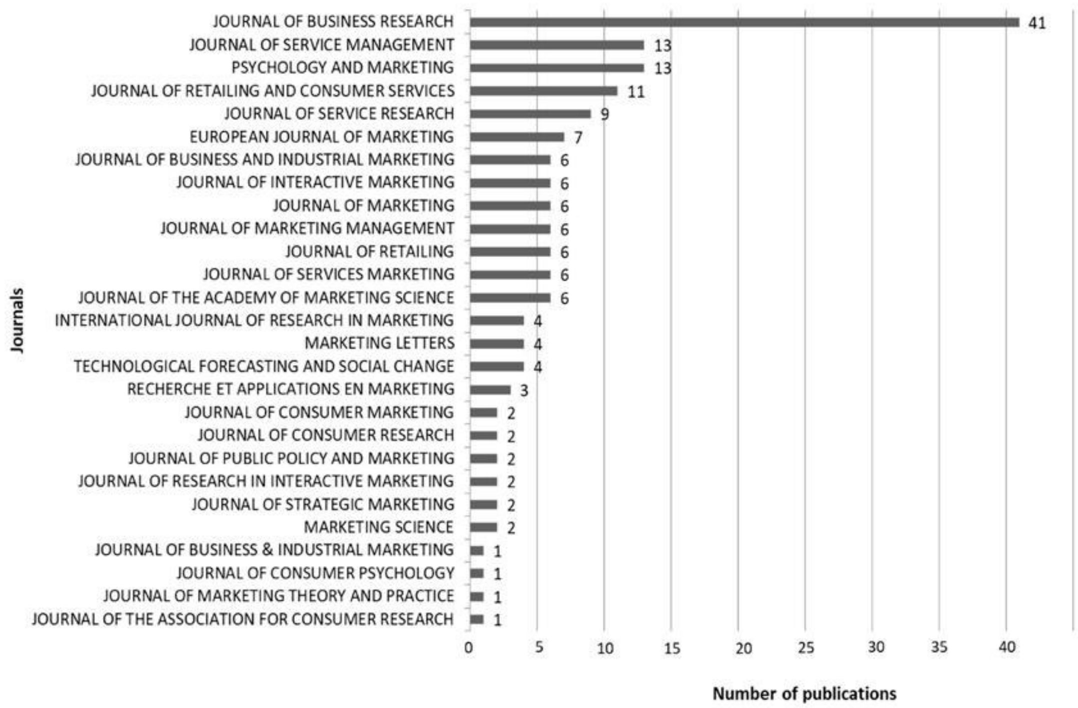
Figure 3 Year-wise distribution of publications



The advancement of academic interest in this area relies on journals that frequently publish articles positioned at the intersection of marketing and AI. In this regard, Figure 4 presents an overview of the most relevant sources considered in the present literature review based on the number of articles they have published. The *Journal of Business Research* has published the most articles on AI and marketing. The next two most relevant journals in terms of number of publications are the *Journal of Service Management* and *Psychology and*

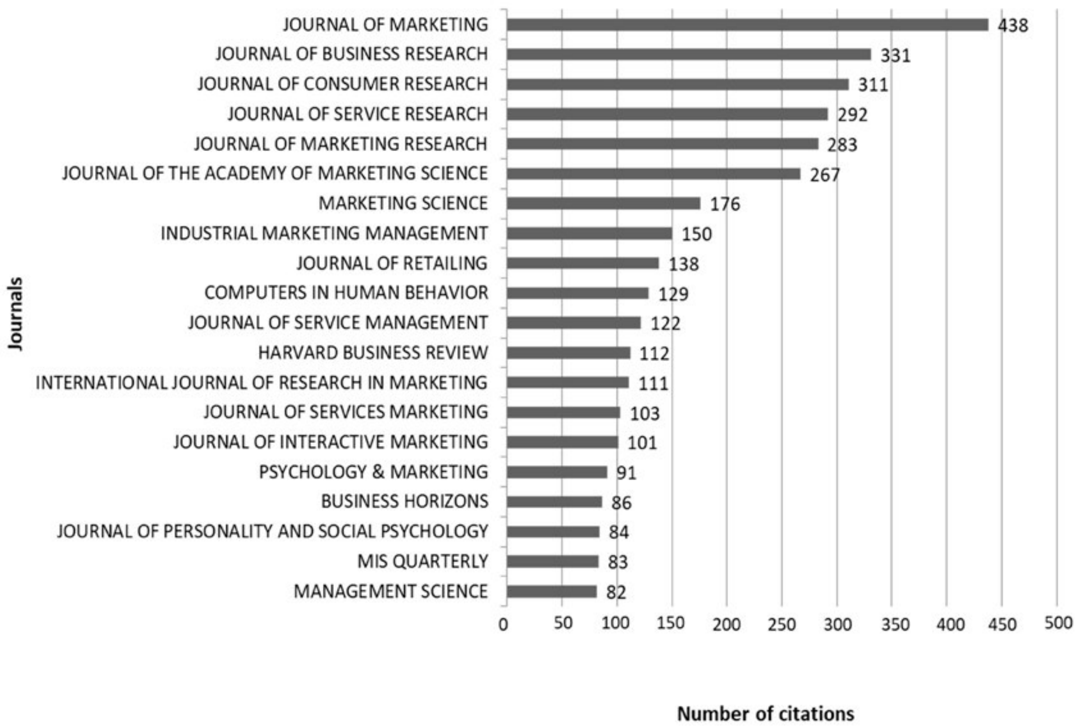
Marketing. Interestingly, A+ and Tier 1 journals (FNEGE) (e.g., the *Journal of Marketing, Journal of Retailing,* and *Journal of Service Research*) do not appear among the top three. In this regard, low-ranked journals seem to be more likely to publish articles on new, innovative topics than top-ranked journals, which are more reluctant and risk adverse.

Figure 4 Most relevant sources



In contrast, Figure 5 presents the most frequently locally cited sources from the reference lists, thus giving an overview of the journals most frequently cited in the reference lists of the selected papers. Despite its lower number of publications, the most frequently cited journal is the top-ranked *Journal of Marketing*, which is followed by *Journal of Business Research* and *Journal of Consumer Research.*

Figure 5 Most cited sources



In addition, we show the 20 most frequently globally cited documents in the field (Table 2). Global citations refer to the total citations (TC) that an article included in a collection has received from documents indexed on a bibliographic database (Scopus). Our global citation score provides an overview of the landmark publications in the marketing field concerning AI. The most frequently cited paper in the database is by Grewal et al. (2017), namely, "The Future of Retailing", and it was published in the *Journal of Retailing*. In this paper, the authors discuss the use of technology, big data, AI, and analytics in retail environments. The second most frequently cited paper is by Huang and Rust (2018), namely, "Artificial Intelligence in Service", and it was published in the *Journal of Service Research.* Here, the authors discuss different levels of AI (mechanical, analytical, intuitive and empathetic), offering managerial insights to help firms implement this technology. The third most frequently cited paper is by Wirtz et al. (2018), namely, "Brave new world: service robots in the frontline", and it was published in the *Journal of Service Management*. In this paper, the authors explore the role that service robots may play in the future and propose a research agenda for service researchers.

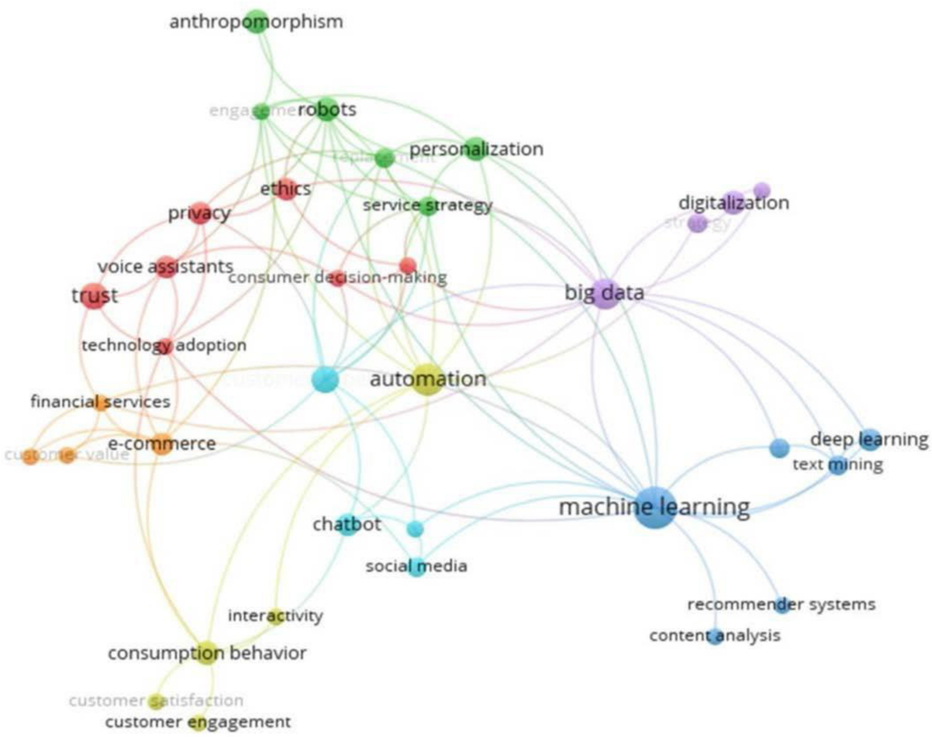
Table 2 Landmark publications

Paper	TC	TC per Year
Grewal et al., 2017, *Journal of Retailing*	317	63.4
Huang and Rust, 2018, *Journal of Service Research*	294	73.5
Wirtz et al., 2018, *Journal of Service Management*	230	57.5
Davenport et al., 2020, *Journal of the Academy of Marketing Science*	83	41.5
Buhalis et al., 2019, *Journal of Service Management*	82	27.3
Longoni et al., 2019, *Journal of Consumer Research*	70	23.3
Ehret and Wirtz, 2017, *Journal of Marketing Management*	62	12.4
De Keyser et al., 2019, *Journal of Service Management*	61	20.3
Nilashi et al., 2015, *Journal of Retailing and Consumer Services*	56	8.0
Steinhoff et al., 2019, *Journal of the Academy of Marketing Science*	52	17.3
Luo et al., 2019, *Marketing Science*	48	16
Balducci and Marinova, 2018, *Journal of the Academy of Marketing Science*	48	12
Paschen et al., 2019, *Journal of Business and Industrial Marketing*	33	11
McIntyre et al., 1993, *Journal of Retailing*	33	1.1
Krabuanrat and Phelps, 1998, *Journal of Business Research*	29	1.2
Kim et al., 2019, *Marketing Letters*	28	9.3
Steckel et al., 2005, *Marketing Letters*	28	1.6
Sjödin et al., 2020, *Journal of Business Research*	25	12.5
Glushko and Nomorosa, 2013, *Journal of Service Research*	25	2.7
Steinberg and Plank, 1987, *Journal of The Academy of Marketing Science*	25	0.7

3.2. Science Mapping Analysis: Keyword Clustering

Using Vosviewer, we extract the conceptual structure of the literature based on a co-occurrence network of keywords. This map of keyword co-occurrences (Figure 6) shows that there are a total of seven clusters.

Figure 6 Map of keywords co-occurrence



The first cluster (blue) features the following keywords: content analysis, deep learning, machine learning, natural language processing, recommender systems and text mining. Thus, we call this cluster "AI techniques and applications". The papers in this category offer methodological contributions by applying or analyzing AI techniques (Table 3).

The second cluster (green) features the following keywords: anthropomorphism, engagement, personalization, replacement, robots, and service strategy. The papers belonging to this cluster mainly use theories related to anthropomorphism (e.g. Karimova and Goby 2021; Kim et al. 2019; Mende et al. 2019) and social presence (e.g. McLean et al. 2021; Pitardi and Marriott 2021; van Doorn et al. 2017) to investigate customer engagement, human replacement and service strategy (McLean et al. 2021; Moriuchi 2019). We call this cluster "human-AI interactions in service settings" (Table 3).

The third cluster (red) features the following keywords: consumer decision-making, ethics, privacy, robotics, technology adoption, trust, and voice assistants. The papers in this cluster mainly focus on the ethics of AI and technology adoption (Du and Xie 2020), trust in technology (Hasan et al. 2020) and issues related to privacy (Thomaz et al. 2020). Thus, we call this cluster “AI ethics” (Table 3).

The fourth cluster (yellow) features the keywords automation, consumption behavior, customer engagement, customer satisfaction, and interactivity. The papers in this cluster mainly investigate consumption behaviors and psychological mechanisms related to automation and AI technology (Table 3). They often apply psychological theories to investigate consumers’ intentions to adopt new technologies such as autonomous vehicles (Huang and Qian 2021), consumers’ engagement and interactivity (Moriuchi 2021), consumers’ satisfaction (Gäthke 2020) and decision-making in the era of AI (Dellaert et al. 2020). We call this cluster “consumer behaviors and psychology in the era of AI”.

The fifth cluster (purple) features the keywords big data, digital transformation, digitalization, and strategy, mainly focusing on how companies adapt to AI. Thus, the papers in this cluster focus on topics related to digital transformation and the way AI and big data affect companies’ strategies (e.g. Fossen and Sorgner 2021; Pemer 2020). We call this cluster “AI, company transformation and strategy” (Table 3).

The sixth cluster (light blue) focuses on the keywords chatbot, customer experience, sentiment analysis, and social media. Thus, the papers in this cluster mainly focus on AI applications for automated customer relationship management via social media (e.g. Kaiser et al. 2020). We call this cluster “AI and social media management” (Table 3).

The seventh cluster (orange) features the keywords customer value, e-commerce, financial services, and service quality, mainly focusing on how financial services and economic transactions are affected by AI technologies (e.g. Manser Payne et al. 2021). We call this cluster "AI, e-commerce and financial services" (Table 3).

Table 3 Exemplary studies for each cluster

Cluster	Title/Jnls	Keywords	Exemplary studies
1	AI techniques and applications *European Journal of Marketing, International Journal of Research in Marketing, Journal of business research, Journal of retailing, Journal of marketing management*	Content analysis Deep learning Machine learning NLP Recommender systems Text mining	Albrecht et al. 2021; Allal-Chérif et al. 2021; Alpar 1991; Balducci and Marinova 2018; Baray and Pelé 2020; Berger et al. 2020; Bromuri et al. 2020; Chinchanachokchai et al. 2021; Cooke and Zubcsek 2017; De Carlo et al. 2021; Humphreys and Wang 2018; Key and Keel 2020; Kietzmann and Pitt 2020; Krafft et al. 2020; Lee et al. 2020; Marchand and Marx 2020; Martins et al. 2020; McIntyre et al. 1993; Mustak et al. 2021; Ordenes and Zhang 2019; Paschen et al. 2019; Paschen et al. 2020; Pitt et al. 2018; Pitt et al. 2020; Pymont et al. 1988; Ville 1997; Wilson and Bettis-Outland 2019; Winters 1991; Zaki and McColl-Kennedy 2020; Zhu et al. 2021
2	Human-AI interactions in service encounters *Journal of Service Research, Journal of Services Marketing, Psychology and Marketing, Journal of Service Management, Recherche et Applications en Marketing*	Anthropomorphism Engagement Personalization Replacement Robots Service Strategy	Belanche et al. 2020; Borau et al. 2021; De Keyser et al. 2019; Fernandes and Oliveira 2021; Gelbrich et al. 2021; Glushko and Nomorosa 2013; Granulo et al. 2021; Haenlein and Kaplan 2021; Hasan et al. 2020; Henkel et al. 2020; Hildebrand et al. 2020; Hollebeek et al. 2020; Huang and Rust 2018, 2021a, 2021b;Hult et al. 2020; Karimova and Goby 2021; Young Kim et al. 2019; Kot and Leszczyński 2020; Longoni et al. 2019; Xueming Luo et al. 2019; McLean et al. 2021; Mende et al. 2019; Moriuchi et al. 2020; Moriuchi 2021; Pitardi and Marriott 2021; Prentice et al. 2020; Ramadan et al. 2021; Robinson et al. 2020; Sampson and Chase 2020; Schepers and van der Borgh 2020; Schweitzer et al. 2019; Silva and Bonetti 2021; Söderlund 2020; Sowa et al. 2021; van Doorn et al. 2017; Whang and Im 2021; Wirtz et al. 2018; Yun et al. 2021

3	AI and ethics *Journal of Marketing, Journal of Public Policy and Marketing, Journal of Business Research, Journal of consumer research*	Consumer decision-making Ethics Privacy Robotics Technology adoption Trust Voice assistants	Banker and Khetani 2019; Belk 2016; Bock et al. 2020; Borau et al. 2021; Braganza et al. 2020; Davenport et al. 2020; Dholakia and Firat 2019; Di Vaio et al. 2020; Du and Xie 2020; Ferreira et al. 2020; Guha et al. 2021; Hildebrand et al. 2020; Kashyap 2021; Letheren et al. 2020; Loureiro et al. 2020; Mele et al. 2021; Murtarelli et al. 2021; Novak 2020; Pizzi et al. 2020; Poole et al. 2021; Puntoni et al. 2021; Bernd Schmitt 2020; Stahl et al. 2021)
4	Consumer behaviors and psychology in the era of AI *Journal of Marketing, Journal of Retailing, Journal of Service Research, Psychology and Marketing, Marketing letters*	Automation; Consumption behavior; Customer Engagement; Customer satisfaction; Interactivity	Belk 2016; Brill et al. 2019; Butt et al. 2021; Dai and Singh 2020; de Bellis and Venkataramani 2020; Dellaert et al. 2020; Gäthke 2020; Granulo et al. 2021; Hamilton et al. 2021; Hollebeek et al. 2020; Huang and Qian 2021; Klaus and Zaichkowsky 2020; Lalicic and Weismayer 2021; Longoni et al. 2019; Longoni and Cian 2020; Mele et al. 2021; Perez-Vega et al. 2021; Pillai et al. 2020; Poushneh 2021; Ramadan et al. 2021; Rodgers et al. 2021; Smith 2020; Söderlund 2020; Steckel et al. 2005; Tassiello et al. 2021; Tigre Moura and Maw 2021; Weihrauch and Huang 2021
5	AI, company transformation and strategy *Journal of business research, Journal of the Academy of Marketing Science, International Journal of research in marketing*	Big data; Digital transformation; Digitalization; Strategy	Battisti and Brem 2020; Bertani et al. 2021; Bonnin and Alfonso 2019; Buhalis et al. 2019; Burström et al. 2021; Davenport et al. 2020; De Bruyn et al. 2020; de Ruyter et al. 2020; Ehret and Wirtz 2017; Fernandez-Rovira et al. 2021; Fossen and Sorgner 2021; Grewal et al. 2017; Guha et al. 2021; Huang and Rust 2021b; Kozinets and Gretzel 2021; Krabuanrat and Phelps 1998; Langley et al. 2021; Leone et al. 2021; Loureiro et al. 2020; Luo et al. 2021; Makarius et al. 2020; Manser Payne et al. 2021; Meyer et al. 2020; Mithas et al. 2020; Pemer 2020; Rampersad 2020; Rust, 2020; Sampson 2021; Shrestha et al. 2021; Sisodia 1991; Sjödin et al. 2020; Sohrabpour et al. 2021; Sowa et al. 2021; Steinberg and Plank 1987
6	AI and social media management *Journal of interactive marketing,*	Chatbot; Customer experience; Sentiment analysis; Social media	Capatina et al. 2020; Chuah and Yu 2021; Dholakia and Reyes 2018; Hoyer et al. 2020; Kaiser et al. 2020; Libai et al. 2020; Pantano and Pizzi 2020; Sidaoui et al. 2020; Verma et al. 2021; Wilson-Nash et al. 2020

	Psychology and marketing		
7	AI, e-commerce and financial services *Journal of the Academy of Marketing Science, Journal of Business Research, Journal of Services Marketing*	Customer value; E-commerce; Financial services; Service quality;	Canhoto 2020; Manser Payne et al. 2021; Manser Payne et al. 2021; Moriuchi 2019; Steinhoff et al. 2019; Zhang et al. 2021

4. Results of the TCCM review

Following the TCCM protocol, we first give an in-depth overview of the main theories used, the contexts and the constructs investigated, and the methodologies applied in each cluster. Next, we discuss the clusters according to the themes that emerge from our analysis.

4.1. Cluster 1: AI Techniques and Applications

The first cluster focuses on AI techniques and applications. This category includes 30 papers, which we review following the TCCM protocol (Table 4). From a theoretical perspective, the authors in this category build on the literature related to AI applications in the marketing context, such as Machine Learning, Artificial Neural Network (ANN) Model Theories, Text Analysis, and Recommender Systems (Berger et al. 2020; Humphreys and Wang 2018; Resnick and Varian 1997). In particular, three main subtopics, which are discussed in the next paragraph, emerge from this cluster: 1) machine learning, deep learning and neural networks; 2) natural language processing; and 3) recommendation algorithms.

Different contexts are investigated by the studies in this cluster, including customers' interactions online (Chinchanachokchai et al. 2021; Marchand and Marx 2020; Paschen et al. 2020) and in service settings such as those related to tourism (De Carlo et al. 2021; Zhu et al. 2021), call centers (Albrecht et al. 2021), healthcare (Martins et al. 2020) and transportation

(Baray and Pelé 2020). Interestingly, 46.4% of the papers in this cluster are conceptual, which highlights the novelty of the field and the need to develop research frameworks to guide researchers (Alpar 1991; Kietzmann and Pitt 2020; McIntyre et al. 1993; Pymont et al. 1988). Concerning the methodology, 46.4% of the papers adopt AI-based methods to conduct their research, such as machine learning, deep learning, text mining, image processing or neural networks (Key and Keel 2020; Lee et al. 2020; Paschen et al. 2020). In this regard, the papers in this category often offer methodological contributions by applying or analyzing AI techniques. In addition, 30% of the papers use behavioral data, which are considered more reliable than traditional declarative data (Albrecht et al. 2021; De Carlo et al. 2021; Lee et al. 2020).

Table 4 TCCM for cluster 1

	No. of studies	%	Exemplary studies
THEORIES			
Automated Text Analysis (Berger et al. 2019; Humphreys and Wang 2017)	3	10.0	Kietzmann and Pitt 2020; Pitt et al. 2020; Zaki and McColl-Kennedy 2020
Recommender Systems (Resnick and Varian 1997)	2	6.7	Chinchanachokchai et al. 2021; Marchand and Marx 2020
Strategic Marketing (Nath and Mahajan 2008)	1	3.3	Key and Keel 2020
Knowledge Management Theory (Detienne and Jackson 2001)	1	3.3	Paschen et al. 2020
ANN Model Theory (Paliwal and Kumar 2009)	1	3.3	Wilson and Bettis-Outland 2019
Machine Learning in Customer Analytics (Yang and Allenby 2003)	1	3.3	Albrecht et al. 2021
Geomarketing-Mix (McCarthy 1960)	1	3.3	Baray and Pelé 2020
Big Data and Marketing Analytics	1	3.3	Gupta et al. 2020
Other theories	7	23.3	Key and Keel 2020; Lee et al. 2020; Bromuri et al. 2020
No guiding theories	12	40.0	Ma and Sun 2020; Mustak 2021; Balducci et al. 2021
TOT	**30**	**100**	
CONTEXT			
Industry			

B2B	2	6.7	Key and Keel 2020; Gupta et al. 2020
B2C:			
Retailing			
Online shopping	4	13.3	Paschen et al. 2020; Marchand and Marx 2020; Chinchanachokchai et al. 2020
Offline shopping	1	3.3	McIntyre et al. 1993
Services industries			
Touristic services	2	6.7	De Carlo et al. 2021; Zhu et al. 2021
Call centers	2	6.7	Albrecht et al. 2021
Pension service providers	1	3.3	Bromuri et al. 2021
Healthcare	1	3.3	Martins et al. 2020
Transportation	1	3.3	Baray and Pelé 2020
Art and culture	1	3.3	Pitt et al. 2020
Industry not explicitly stated	15	50.0	Key and Keel 2020; Kietzmann and Pitt 2020; Lee et al. 2020
Country			
United States	3	10.0	Key and Keel 2020; Wilson and Bettis-Outland 2019; Chinchanachokchai et al. 2021
Germany	1	3.3	Albrecht et al. 2021
Spain and Italy	1	3.3	De Carlo et al. 2021
London	1	3.3	Zhu et al. 2021
Netherlands	1	3.3	Bromuri et al. 2021
Portugal	1	3.3	Martins et al. 2020
France	1	3.3	Baray and Pelé 2020
Malasya	1	3.3	Nilashi et al. 2015
South Africa	1	3.3	2019
Country not reported	19	63.3	Kietzmann and Pitt 2020; Lee et al. 2020; Paschen et al. 2020
TOT	**30**	**100**	
CHARACTERISTICS VARIABLES			
Independent			
knowledge creation	2	6.7	Paschen et al. 2019; Chinchanachokchai et al. 2021
Big data	1	3.3	Paschen et al. 2019
Decision making	1	3.3	Paschen et al. 2019
Website quality	1	3.3	Nilashi et al. 2015
Dependent			
Knowledge creation	1	3.3	Paschen et al. 2019
Decision making	1	3.3	Paschen et al. 2019
Recommender system	1	3.3	Chinchanachokchai et al. 2021
Service quality	1	3.3	Nilashi et al. 2015
METHOD			
Research approach			
Conceptual	14	46.7	Alpar, 1991; Kietzmann and Pitt, 2020; McIntyre et al., 1993; Mustak et al., 2021;

			Pymont et al., 1988
Qualitative	1	3.3	Kumar et al., 2021
Quantitative	11	36.7	Albrech et al. 2021 ; Paschen et al. 2019 ; Wilson and Bettis-Outland 2019;
Mixed-methods	4	13.3	Key and Keel 2020; Lee et al. 2020; Paschen et al. 2020; Pitt et al. 2021
Research method			
Conceptual framework development	12	40.0	Alpar, 1991; Kietzmann and Pitt, 2020; McIntyre et al., 1993; Pymont et al., 1988
Literature review	2	6.7	Kumar et al., 2021; Mustak et al., 2021
AI-based method (ML, DL, Text Mining, Image Processing, ANN)	14	46.7	Key and Keel, 2020; Lee et al., 2020; Paschen et al. 2020
Survey	1	3.3	Paschen et al. 2019
Interviews	1	3.3	Kumar et al. 2021
Analysis			
ANN, ANP and Fuzzy logic models	5	16.7	Wilson and Bettis; Bromuri et al; De Carlo Nilashi et al. ; Baray and Pelé 2020
Automated text analysis	5	16.7	Key and Keel: Pitt et al. ; Zhu et al.
PLS-SEM, OLS, Regressions	3	9.9	Marchand and Marx 2020; Paschen et al. 2019; Wilson and Bettis-Outland 2019
Bibliometric and scientometric	1	3.3	Mustak et al. 2021
Interview thematic analysis	1	3.3	Kumar et al. 2021
Strategic options development and analysis (SODA)	1	3.3	Martins et al. 2020
Other analytical (conceptual papers)	14	46.7	Alpar 1991; Kietzmann and Pitt 2020
Type of data			
Declarative	4	13.3	Paschen et al. 2019; Pitt et al.; Key and Keel
Behavioral	9	30.0	Albrecht et al. 2021; De Carlo et al., 2021; Lee et al., 2020
Secondary data	2	6.7	Mustak et al. 2021; Wilson and Bettis-Outland, 2019
Other (georeferenced data and articles for conceptual papers)	15	50.0	Baray and Pelé 2020; Kietzmann and Pitt 2020; Krafft et al. 2020
TOT	**30**	**100**	

Note: concerning the methodology some papers belong to more categories (Kumar et al. 2020; Pitt et al. 2020). All the percentages are calculated over the total number of papers in the cluster.

4.1.1. Machine Learning, Deep Learning and Neural Networks

The first subtopic of this cluster is machine learning (ML). Mitchell et al. (1991) define machine learning as computer programs that learn from experience with respect to a certain class of tasks and performance measures. Machine learning has become the main paradigm of

AI research, and it is typically considered a subfield of AI (Ma and Sun 2020). Machine learning can be supervised, unsupervised or semisupervised. Ma and Sun (2020, p. 484) state that supervised learning involves “a training dataset where both the input, a collection of variables commonly denoted as X, and the output, a target variable commonly denoted as Y, are observed”. The goal of supervised learning is prediction. In contrast, in the case of unsupervised learning, “the training dataset contains only the input variables, while the output variables are either undefined or unknown” (Ma and Sun 2020, p. 484). Thus, researchers employing this approach aim to find and extract hidden patterns. Semisupervised learning represents the middle ground between these two categories, as in this case, the output of only a subset of data is known. Ma and Sun (2020) provide an overview of common machine learning tasks and methods and compare them with the statistical and econometric methods traditionally used by marketing researchers. These authors highlight the advantages and disadvantages of using machine learning methods. On the one hand, if machine learning is able to process large-scale and unstructured data, then this approach will provide flexible model structures that yield strong predictive performance; on the other hand, transparency and algorithm interpretability are major issues that need to be addressed.

Additionally, machine learning algorithms have been successfully applied in the field of marketing research. For instance, Albrecht et al. (2021) investigate the capabilities of machine learning models for intradaily call center arrival forecasting with respect to prediction accuracy and practicability. These authors suggest that one of the main reasons that machine learning approaches outperform traditional time series models is their ability to capture additional information due to the inclusion of predictor variables. Thus, machine learning techniques not only are better than traditional models in terms of outlier forecast accuracy but also exhibit improved overall prediction performance over longer time periods.

Additionally, Bromuri et al. (2020) apply AI techniques to investigate service encounters in call centers. In particular, these authors develop a deep learning model to predict service agents' emotions during service encounters. Deep learning is a subcategory of machine learning that is defined as a "learning method with multiple levels of representation obtained by composing simple but non-linear modules that each transform the representation at one level into a representation at a higher, slightly more abstract level" (Ma and Sun 2020 p. 483). By applying this deep learning emotion classifier, researchers are able to identify real-time service agent stress from emotion patterns in voice-to-voice service interactions. The model reaches a balanced accuracy of 68% in terms of predicting discrete emotions in service interactions and is able to predict service agent stress with a balanced accuracy of 80%. Thus, these AI applications might have great potential for managers and employees in relation to continuously monitoring the stress levels of service agents and improving their work conditions and well-being.

Deep unsupervised algorithms have also been used to design collaborative strategies in business environments (De Carlo et al. 2021). In particular, De Carlo et al. (2021) propose an innovative application of a deep unsupervised artificial neural network algorithm, namely, the autoactive map method, to investigate the complex and dynamic competitive settings of tourism destinations, which are characterized by the inclusion of many stakeholders. In addition, Wilson and Bettis-Outland (2019) investigate the use of artificial neural network (ANN) models to improve analyses of B2B marketing research data. They provide a series of tests that compare ANN models and competing predictive models, offering new insights on ANNs for business and academic researchers.

4.1.2. Natural Language Processing

The second subtopic of this cluster is natural language processing (NLP) techniques. NLP approaches are designed to reveal the linguistic relationships in sentences through the use of machine learning tools (Berger et al. 2020). One application of NLP is text mining, which uses a set of NLP and machine learning techniques to process textual documents, identify the patterns within a structure, and provide evaluations and interpretations of output to produce insights (Zaki and McColl-Kennedy 2020). Text analysis can be used to examine psychological and sociological constructs in consumer-produced digital text by enabling discovery or providing ecological validity (Humphreys and Wang 2018). For instance, Pitt et al. (2020) propose a new approach to conducting psychographic consumer segmentations. Specifically, using a mixed-methods approach over several studies, the authors develop a typology that can be applied to fine art collectors. First, the authors analyze qualitative data gathered via semistructured interviews with art collectors. Second, they quantitatively analyze the interviews using NLP and automated text analysis. Through their research, the authors present a new detailed methodology involving the use of textual data to identify measurable market segments for which targeted strategies can be developed (Pitt et al. 2018; Pitt et al. 2020). Moreover, NLP and text mining are often used to investigate consumers' sentiments in the contexts of online discourses, blogs, reviews and social media (Berger et al. 2020; Humphreys and Wang 2018; Paschen et al. 2020; Zhu et al. 2021). For instance, Paschen et al. (2020) use a hybrid content analysis method to analyze Twitter data, investigating the motivations of everyday consumers who participate in the annual "Buy Nothing Day". With their research, these authors contribute to an understanding of the methodological approaches that can be used to gain market intelligence from unstructured data using human and AI methods. In this regard, Balducci and Marinova (2018) propose that the structures of data range on a continuum from highly unstructured to highly structured. Unstructured data such as video data contain many simultaneous data points (nonverbal cues, acoustic vocal cues, and spoken words) that flow concurrently. In such cases, researchers assign values to these data, manually or automatically, before proceeding with an analysis (Balducci and Marinova 2018). Structured data such as survey data require relatively little or almost no effort on the part of a researcher in terms of preparation for analysis. According to Kietzmann and Pitt (2020), merging different forms of unstructured data provides a wealth of insight that is neglected by existing content analysis methods. In this regard, Lee et al. (2020) explore how AI, specifically the IBM Watson system, can be used for content analysis in the context of marketing research, comparing this approach with manual and computer-aided (non-AI) methods. The author suggests that AI-enabled automated text analyses provide clear advantages over manual and computer-aided approaches with high levels of reliability and validity and a moderate level of efficiency. In addition, to improve the quality of text analyses, Berger et al. (2020) suggest that there are different types of text analysis, which are used according to the type of research questions investigated, require specific and adapted tools, and have specific benefits and limitations. For instance, entity (word) extraction requires tools such as dictionaries and lexicons (e.g., LIWC, EL 2.0, SentiStrength), and it is used for brand buzz monitoring, predictive models with textual input, the extraction of psychological states and traits, sentiment analysis, and consumer and market trends. Another approach is topic extraction, which requires tools such as latent sematic analysis (LSA) or latent dirichlet allocation (LDA) and can be used to extract topics from textual data to identify consumer trends and needs. This approach often provides useful summaries of data and permits the use of traditional statistical methods in subsequent analyses. Finally, relation extractions facilitate the identification of relationships among words through the use of tools such as entity co-occurrence and supervised machine learning in the context of, for instance, market mapping (Berger et al. 2020).

In addition to text, pictures and images can be used as units of analysis. In this regard, Ordenes and Zhang (2019) focus on image mining. First, these authors propose a state-of-the-art text and image mining business research method by providing a detailed conceptual and technical review of both methods. Second, they provide several suggestions related to the use of new sources of structured and unstructured data such as customer reviews, social media images, employee reviews and emails; the measurement of new constructs; and the use of relatively modern methods such as deep learning.

4.1.3. Recommendation Algorithms

The third subtopic concerns recommendation algorithms. Recommender system algorithms are mainly used to make product recommendations or deliver personalized content to users (Chinchanachokchai et al. 2021). Marchand and Marx (2020) suggest that there are three broad categories of recommendation systems: collaborative filtering systems, content-based filtering systems, and hybrid approaches. User-based collaborative filtering (CF) refers to the process of evaluating and filtering products based on the opinions and preferences of an entire user base to produce recommendations (Chinchanachokchai et al. 2021; Marchand and Marx 2020). This approach is widely used by many companies, such as YouTube, Netflix, and Spotify, to make product or service recommendations to consumers (Chinchanachokchai et al. 2021). In contrast, content-based (CB) approaches rely on the attribute preferences of a target user to identify items similar to those that the user has preferred in the past. Based on item descriptions and user interests, this type of recommender system learns individualized product profiles from item descriptions and makes recommendations. Thus, it does not need to match users with their interests. Between these two approaches, there are hybrid systems that generate recommendations using a combination of CF and CB methods (Marchand and Marx 2020).

Marketing researchers have analyzed recommendation algorithms to improve their predictive power. For instance, using a combination of content-based and collaborative filtering to analyze two real-world datasets with more than 100 million product ratings, Marchand and Marx (2020) propose a method that outperforms established recommender approaches in terms of predictive accuracy. According to the authors, the ability to provide actionable explanations is a positive ethical requirement of AI systems. Additionally, Chinchanachokchai et al. (2021) construct a recommendation program using review data from existing online communities to investigate the effect of consumer knowledge and expertise on consumer preferences regarding recommendation systems. The authors suggest that on the one hand, expert consumers prefer user-based collaborative filtering systems, while on the other hand, among novice consumers, there is no difference between collaborative-based and content-based systems.

4.2. Cluster 2: Human-AI Interactions in Service Encounters

The studies in the second cluster concentrate mainly on interactions between customers and AI agents in service encounters. In this cluster, we review 38 papers (Table 5). The predominant theoretical framework is related to Anthropomorphism Theories (Aggarwal and McGill 2007; Epley et al. 2007), and this is followed by Social Perception Theory (Fiske et al. 2007), Social Presence Theory (van Doorn et al. 2017) and the Theory of Multiple Intelligence and Job Replacement developed by Huang and Rust (2018). Many of these studies investigate virtual assistants and conversational agents (Fernandes and Oliveira 2021; Karimova and Goby 2021; Pitardi and Marriott 2021). The predominant countries of interest are the United States (Belanche et al. 2020; Kim et al. 2019; Moriuchi et al. 2021) and the UK (Borau et al. 2021; Hasan et al. 2020; Pitardi and Marriott 2021); this highlights these researchers' tendency to investigate English-speaking countries. Overall, 52.6% of the papers in this category adopt traditional quantitative approaches (Fernandes and Oliveira 2021; Gelbrich et al. 2021; Hasan et al. 2020), and most of them use experimental designs (34.2%, Gelbrich et al. 2021; Kim et al. 2019; Luo et al. 2021). In this regard, declarative data are still preferred over behavioral data (Gelbrich et al. 2021; Hasan et al. 2020; McLean et al. 2021).

In the next section, we first describe this cluster, defining AI service agents according to the marketing literature. Next, we discuss the three subtopics of this cluster: anthropomorphism and human-likeness; gender and identity; and human-bot replacement.

Table 5 TCCM for cluster 2

	No. of studies	%	Exemplary studies
THEORIES			
Anthropomorphism Theory (Aggarwal and McGill 2007; Epley et al. 2007)	9	23.7	Belk 2016; Pizzi et al. 2020; Schweitzer et al. 2019
Social Perception Theory (Fiske et al. 2007)	5	13.2	Henkel et al. 2020; Kim et al. 2019; Wirtz et al. 2018
Social Presence Theory (van Doorn et al., 2017)	4	10.5	De Keyser et al. 2019; McLean et al. 2021; Wirtz et al. 2018
Theory of Multiple Intelligence and Job Replacement (Huang and Rust 2018)	4	10.5	Huang and Rust 2021a; 2021b; 2021c; Bock et al. 2020
Self-Extension Theory (Belk 1988)	2	5.3	Granulo et al. 2021; Schweitzer et al. 2019
Coping (Folkman and Lazarus 1984) and Emotion Regulation (Grandey 2003)	2	5.3	Bromuri et al. 2020; Gelbrich et al. 2021; Henkel et al. 2020
Trust Theories (Lee and See 2004; McKnight and Chervany 2001)	2	5.3	Hasan et al. 2020; Karimova and Goby 2021
Service Robots Acceptance Theory (Wirtz et al. 2018)	2	5.3	Pizzi et al. 2020; Fernandes and Oliveira 2021
Attribution Theory (Weiner 2000)	1	2.6	Belanche et al. 2020
Evolution Theory (Darwin 1859)	1	2.6	Yun et al. 2021
Other theories	7	18.4	Schepers and van der Borgh 2020; Sowa et al. 2021
TOT	**38**		
CONTEXT			
Industry			
Virtual assistants for daily activities	11	28.9	Fernandes and Oliveira 2021;

			Karimova and Goby 2021; Pitardi and Marriott 2021
Health industry	3	7.9	Gelbrich et al. 2021; Borau 2021; Yun et al. 2021)
Hospitality	3	7.9	Belanche et al. 2020; Glushko and Nomorosa 2013; Prentice et al. 2020
Online shopping	2	5.3	McLean et al. 2021; Moriuchi 2021
Financial services	2	5.3	Henkel et al. 2020; Sowa et al. 2021
Art and culture	2	5.3	Granulo et al. 2021; Söderlund 2020
Telecommunication and transportation	1	2.6	Pizzi et al. 2020
Food and nutrition	1	2.6	Whang and Im 2021
Real estate	1	2.6	Balakrishnan and Dwivedi 2021
Fashion	1	2.6	Silva and Bonetti 2021
Industry not explicitly stated	12	31.6	Huang and Rust 2018; 2020; Schepers and van der Borgh 2020
Country			
Unites States	**7**	18.4	Belanche et al. 2020Kim et al. 2019 ; Moriuchi et al. 2021 ;
UK	5	13.2	Borau et al. 2021 ; Hasan et al. 2020 Pitardi and Marriot 2021
Netherland	1	2.6	Henkel et al. 2020
Asia	2	5.3.	Luo et al. 2019 ; Karimova et al. 2020
Australia	1	2.6	Prentice et al. 2020
Not specified	25	65.8	De Keyser et al. 2019; Huang and Rust 2021a; Kot and Leszczyński 2020
TOT	**38**		
CHARACTERISTICS VARIABLES			
Independent			
Anthropomorphism	5	13.2	Fernandez and Oliveira 2020; Pizzi et al. 2021; Wirtz et al. 2018
Ease of use, usefulness, social norms	4	10.5	Wirtz et al. 2018; Pitardi and Marriot 2021; Fernandez and Oliverira 2020
Identity of the agent (human versus machine)	4	10.5	Belanche et al. 2020; Balakrishnan and Dwivedi 2021; Henkel et al. 2020; Bromuri et al. 2020
Trust	3	7.9	Hasan et al. 2020; Wirtz et al. 2020; Balakrishnan and Dwivedi 2021
Gender of the agent	1	2.6	Borau et al. 2021
Privacy concerns	1	2.6	Pitardi and Mariott 2021
Dependent			
Acceptance of AI	5	13.2	Fernandes and Oliveira 2021; Pizzi et al. 2020; Yun et al. 2021)
Usage intention	2	5.3	Balakrishnan and Dwivedi 2021; Moriouchi et al. 2020
Competence and warmth	2	5.3	Kim et al. 2019; Borau et al. 2021

Customer Satisfaction	3	7.9	Gelbrich et al. 2021; Pizzi et al. 2021
Trust	2	5.3	Balakrishnan and Dwivedi 2021; Borau et al. 2021
Loyalty	2	5.3	Hasan et al. 2020, Prentice et al. 2020
Attributions	1	2.6	Belanche et al. 2020
Consumer preferences	1	2.6	Granulo et al. 2021
Engagement	1	2.6	Prentice et al. 2020
Mediating			
Engagement	2	5.3	Prentice et al. 2020 ; Moriuchi et al. 2020
Warmth	1	2.6	Gelbrich et al. 2021
Customer Satisfaction	1	2.6	Gelbrich et al. 2021
Perceived performance	1	2.6	Pizzi et al. 2021
Choice difficulty	1	2.6	Pizzi et al. 2021
Privacy concerns	1	2.6	Söderlund et al. 2020
Robot acceptance	1	2.6	Wirtz et al. 2018
Moderating			
Identity of the agent	2	5.3	Gelbrich et al. 2021; Söderlund 2020
Gender	2	5.3	Borau et al. 2021; Schepers 2020
Perceived intelligence	1	2.6	Mc Lean et al. 2020
Anthropomorphism	1	2.6	Kim et al. 2019
Uncertainty avoidance	1	2.6	Schepers 2020
Service outcome	1	2.6	Belanche et al. 2020
Emotional intelligence	1	2.6	Prentice et al. 2020
METHODS			
Research approach			
Conceptual	12	31.6	De Keyser et al. 2019; Huang and Rust 2021a; Kot and Leszczyński 2020
Qualitative	3	7.9	Belk 2016; Karimova and Goby 2021; Ramadan et al. 2021
Quantitative	20	52.6	Gelbrich et al. 2021; Fernandes and Oliveira 2021; Hasan et al. 2020
Mixed-methods	3	7.9	Mc Lean 2021; Pitardi 2021; Sowa et al. 2021
Research method			
Conceptual framework development	11	28.9	Robinson et al. 2020 ; Huang and Rust 2018; 2021a
Literature review	1	2.6	Hult et al. 2020
Meta-analysis	1	2.6	Schepers and van der Borgh 2020
AI-based method (voice recognition)	2	5.3	Bromuri et al. 2020; Henkel et al. 2020; Hildebrand et al. 2020
Survey	5	13.2	Fernandes and Oliveira 2021; Hasan et al. 2020; Pitardi and Marriott 2021
Interviews	6	15.8	Ramadan et al. 2021; Pitardi and Marriott 2021; Schweitzer et al. 2019
Experimental design	13	34.2	Gelbrich et al. 2021; Kim et al. 2019; Luo et al. 2021

Analysis			
Anova, Mavona, Ancova	8	21.1	Belanche et al. 2021; Gelbrich et al. 2021; Kim et al. 2019
PLS-SEM, SEM	9	23.7	Hasan et al. 2020; Moriuchi 2021; Prentice et al. 2020
Deep learning models	2	5.3	Luo et al. 2019; Henkel et al. 2020
Thematic analysis	2	5.3	McLean et al. 2021; Pitardi and Marriott 2021
IAD score	1	2.6	Borau et al. 2021
Meta-analytic correlation	1	2.6	Schepers and van der Borgh 2020
Content analysis	1	2.6	Sowa et al. 2021
Frequency analysis	1	2.6	Silva and Bonnetti 2021
Other analytical methods (conceptual papers and signal processing)	13	34.2	Huang and Rust, 2021a; Kot and Leszczyński 2020; Robinson et al. 2020
Type of data			
Declarative	19	50.0	Gelbrich et al. 2021; Mc Lean et al. 2021; Hasan et al. 2021
Behavioral	5	13.2	Hidelbran et al. 2021; Henkel et al. 2020. Fernandes and Oliveira 2021
Secondary data	1	2.6	Schepers and van der Borgh 2020
Other (conceptual papers and meta-analysis)	13	34.2	De Keyser et al. 2019; Huang and Rust 2021a; Kot and Leszczyński 2020
TOT	**38**	**100**	

Note: concerning the theoretical framework, some papers belong to more categories (Pizzi et al. 2021; Bromuri et al. Borau et al. 2021). Concerning the industry, some papers belong to more categories (Pizzi et al. 2021). Concerning the methodology, some papers belong to more categories (Pitardi and Mariott 2021; Sowa et al. 2021; Mc Lean et al. 2021). The percentages are calculated over the total number of papers in the cluster (38)

4.2.1. Defining AI Service Agents

The configuration of technology to provide value in internal and external service environments through flexible adaptation is referred to as “service AI” (Bock et al. 2020, p. 318). There are many technological enablers of service AI: service robots, chatbots, virtual agents and virtual assistants (Bock et al. 2020). Service robots are defined as “system-based autonomous and adaptable interfaces that interact, communicate and deliver service to an organization’s customers” (Wirtz et al. 2018, p. 909). According to Bock et al. (2020), robots can be programmed to carry out a series of actions, movements or tasks to provide human-like service delivery. Virtual agents are computer-generated characters designed to function as customer service representatives (Bock et al. 2020). Chatbots, which are often called virtual agents, are automated programs that interact with humans, processing textual data and providing appropriate responses to consumers' requests and queries typically through a chat platform (Bock et al. 2020). In addition to these technologies, there are virtual assistants, which can be voice-based, responding to voice commands and performing tasks such as creating to-do lists, managing schedules and placing phone calls. Well-known examples of virtual assistants include Apple's Siri, Amazon's Alexa, Microsoft's Cortana, and Google Now (Bock et al. 2020). These technologies can also be referred to as conversational agents, which are defined as physical or virtual autonomous technological entities capable of exhibiting reactive and proactive behavior in their environments, and they are able to accept natural language as input and generate natural language as output to engage in conversation with users (De Keyser et al. 2019). According to De Keyser et al. (2019), conversational agents come in various forms that range along a reality–virtuality continuum: at the reality end of the continuum, there are physically embodied conversational agents – these are often called social robots (Mende et al. 2019); on the virtual end of the continuum, there are disembodied conversational agents, which include voice-based assistants and chatbots (De Keyser et al. 2019).

In this review, we use the general term AI service agent to refer to all these technological enablers of service AI. As it is predicted that AI agents will be employed in an increasing variety of customer-facing situations, an increasing number of academics have begun investigating human-AI interactions within many different service contexts and through different theoretical lenses (Kim et al. 2019).

4.2.2. Anthropomorphism and Human-Likeness

One of the most recurrent topics in AI research is anthropomorphism, defined as a process of inductive inference where people attribute human-like traits to nonhuman agents (Epley 2018). A human-like appearance evokes a human schema, and human-like behaviors lead to attributions of a “mind” (Aggarwal and McGill 2007; Kim et al. 2019; MacInnis and Folkes 2017). A vast stream of research highlights the benefits of attributing human-like characteristics to machines (e.g., Mende et al. 2019; Moriuchi 2021). In this regard, drawing on anthropomorphism and parasocial interaction theory (Horton and Wohl 1956), Whang and Im (2021) investigate the relationship between consumers and AI-powered voice assistants and the way these technologies affect consumers’ evaluations of recommended products in shopping environments. Through two experiments, the authors suggest that when voice assistants possess strong anthropomorphic cues, they are perceived to be human-like and that this facilitates the formation of parasocial relationships with such AI agents and the acceptance of AI recommendations. In addition to acceptance of AI, research shows that anthropomorphism positively affects engagement with AI agents (Moriuchi 2021) and with brands (McLean et al. 2021). Moreover, Pitardi and Marriott (2021) suggest that on the one hand, the functional elements of voice-based virtual assistants, such as their usefulness and ease of use, drive users' attitudes regarding using virtual assistants. On the other hand, social attributes, particularly social presence - which refers to the “extent to which technology makes customers feel the presence of another social entity” (van Doorn et al. 2017) - and social cognition - defined as the way that individuals process, store, and apply information about other people (Fiske et al. 2007)- are fundamental to developing trust relationships with agents. Similarly, Karimova and Goby (2021) and Schweitzer et al. (2019) show that in human-human relationships as well as human-AI agent interactions, trust is fundamental to developing relationships with agents. Schweitzer et al. (2019) investigate voice-based assistants by drawing from research on anthropomorphism and extended-self theory (Belk

1988). According to these authors, interactions with voice-assistants are relatively likely to increase when consumers feel in control and superior to the devices, as this causes them to enjoy their ability to extend themselves through such interactions. However, the extended use of anthropomorphized virtual assistants as partners might have a negative effect on users' future usage intentions, as they might become disillusioned by such machines' lack of real emotional interaction capacities. In this regard, Prentice et al. (2020) suggest that emotional intelligence plays a critical role in customer-employee interactions. For this reason, customers tend to prefer human employee services over AI. However, Gelbrich et al. (2021) suggest that emotional support offered by a digital assistant can help increase customer satisfaction via perceived warmth. Consistent with Prentice et al. (2020), Granulo et al. (2021) suggest that individuals may prefer human labor in the context of products with higher symbolic value because consumers have stronger uniqueness motives in relatively symbolic consumption contexts. The need for uniqueness and the need to have personalized services seem to be strong drivers of consumers' preferences for human-human interactions (Granulo et al. 2021). In relation to overcoming customers' preferences for humans, research points out that humans prefer to engage with realistic, anthropomorphic AI agents, as they feel able to build parasocial relationships with them. In this regard, Söderlund (2020) suggests that humans have a tendency to assign humanity to an artificial stimulus as long as it has at least minimal human features. Accordingly, Silva and Bonetti (2021) suggest that the interaction modalities between humans and technology must be as realistic as possible.

4.2.3. Gender and Identity

Additionally, the gender and identity of agents seem to affect consumers' preferences regarding AI. Concerning the gender of an AI, research on human–robot interaction has shown that people tend to assign relatively communal qualities to female bots, including characteristics such as warmth, friendliness, and a higher capacity to experience emotions (Borau et al. 2021). In addition, individuals tend to prefer female chatbots over male chatbots because they are perceived as more human and more likely to consider customers' unique needs (Borau et al. 2021). Concerning the identity of an agent, researchers have investigated chatbot identity self-disclosure and its effect on customer purchases (Luo et al. 2019). On the one hand, undisclosed chatbots seem to be as effective as humans in terms of stimulating customer purchases; on the other hand, a disclosure of a chatbot's identity before a machine–customer conversation tends to drastically reduce purchase rates (Luo et al. 2019). Thus, despite the objective competence of an AI agent, there seems to be a negative disclosure effect driven by negative subjective human perceptions regarding machines. This effect has also been found in other contexts. For instance, drawing on evolutionary theory, Yun et al. (2021) investigates the psychological mechanisms that explain consumers' interactions with medical AI and human doctors using behavioral experiments in conjunction with a neuroimaging experiment. These authors suggest that consumers perceive identical personalized conversations offered by a medical AI and a human doctor differently. Their results are also in line with Longoni et al. (2019), who show that consumers are reluctant to utilize AI healthcare providers. Thus, knowing a service agent's gender (male versus female) and the identity (human versus machine) seems to affect consumers' perceptions of their interactions with it. In this regard, individuals seem to have preconfigured judgments and algorithm-aversion biases, as they prefer humans even when machines outperform them (Dietvorst et al. 2015).

4.2.4. Human Replacement

In addition to the studies investigating AI agents' characteristics and the ways in which they affect consumer relationships, another stream of research has focused on how AI agents affect service employees (Hollebeek et al. 2020; Huang and Rust 2018, 2021a, 2021b, 2021c). In this regard, if AI constitutes a major source of innovation, it is increasingly replacing service jobs (Huang and Rust 2018). Thus, Huang and Rust (2018) develop a theory of AI job replacement to describe and predict the way AI is likely to replace tasks and change the ways in which service is provided. First, this theory specifies that four types of intelligence are required for service tasks—mechanical, analytical, intuitive, and empathetic intelligence. Fundamentally, AI job replacement occurs at the task level and affects “low” (easier for AI) intelligence tasks first. For instance, mechanical intelligence, which concerns the ability to automatically perform repetitive tasks, is the first type of task to be replaced by AI. In this phase, first, AI takes on some of the tasks involved in the focal service job. This transition stage is seen as an augmentation rather than a replacement. After this stage, analytical skills, which refer to the ability to process information for problem solving and learn from it, become less important, making intuitive and empathetic skills even more important for service employees. Finally, as AI will eventually have both intuitive and empathetic functions, new forms of human–machine collaboration in the context of service delivery will ultimately be defined, posing a serious challenge to human work (Hung and Rust 2018). Huang and Rust (2021b) suggest that employees should engage in collaborative interactions with AI. In fact, even if AI is better able to perform mechanical and analytical marketing and consumption tasks, human intelligence is still better for tasks that require intuition and empathy. For this reason, relatively low-level AI should initially augment higher levels of human intelligence. Only when AI is endowed with empathy and intuition will replacement be an option. Additionally, consumers should learn to collaborate with AI to benefit from using it at its different levels of intelligence. For instance, at the mechanical level, consumers might use AI to save time and effort when performing mechanical consumption tasks.

4.3. Cluster 3: AI and Ethics

The third cluster refers to the ethics of AI. By applying the TCCM protocol, we review 15 papers that investigate the ethics of AI in the context of marketing and consumer behavior through different theoretical lenses (Table 6): Choice Architecture, Heuristics and Biases (Dietvorst et al. 2015; Kahneman and Tversky 2014); Paradoxes of Technology (Mick and Fournier 1998); Anthropomorphism Theories (Nass and Lee 2001); the Uncanny Valley (Mori 1970); and the Moral Mediation Theory of Technology (Verbeek 2015). Seventy-three percent of the papers are conceptual, which highlights the emerging nature of this research topic and the need to develop a theoretical framework to drive research in this field (Du and Xie 2020; Murtarelli 2021; Novak 2020). For this reason, countries are often not examined. In addition, as discussions surrounding ethics often adopt a macrolevel approach, in the selected papers industries are not examined. Next, we describe various ethical approaches to AI, drawing on a review of the marketing literature.

Table 6 TCCM for cluster 3

	No. of studies	%	Exemplary studies
THEORIES			
Choice Architecture, Heuristics and Biases (Dietvorst et al. 2015; Kahneman and Tversky 2014)	4	26.7	Letheren et al. 2020; Schmitt 2020; Stahl et al. 2021
Paradoxes of Technology (Mick and Fournier 1998)	2	13.3	Du and Xie 2020; Puntoni et al. 2021
Anthropomorphism Theory(Nass and Lee, 2001)	2	13.3	Belk 2016; Murtarelli et al. 2021)
Uncanny Valley (Mori 1970)	1	6.7	Schmitt 2020
Economic Theories of Consumption (Modigliani 1966)	1	6.7	Ferreira et al. 2020)
Organisational Trust (Nedkovski et al. 2017)	1	6.7	Braganza et al. 2020
Moral Mediation Theory of Technology (Verbeek 2015)	1	6.7	Du and Xie 2020
Stakeholder Theory (Donaldson and Preston, 1995)	1	6.7	Du and Xie 2020
S-D Logic (Lusch and Vargo 2014)	1	6.7	Murtarelli et al. 2021
Ethics and Privacy in AI and Big Data (Stahl 2012)	1	6.7	Stahl et al. 2021

The Trolley Problem (Foot 1967)	1	6.7	Novak 2020
Other theories	3	20.0	Braganza et al. 2020; Letheren et al. 2020; Poole et al. 2021
No driving theory	3	20.0	
TOT	**15**	**100**	
CONTEXT			
Country			
Europe	1	6.7	Stahl et al. 2021
UK	1	6.7	Braganza et al. 2020
Portugal	1	6.7	Ferreira et al. 2020
No country	12	80.0	Du and Xie 2020; Murtarelli 2021. Novak 2020
TOT	15		
CHARACTERISTICS VARIABLES			
Independent			
Psychological contract	1	6.7	Braganza et al. 2021
Dependent			
Job engagement	1	6.7	Braganza et al. 2021
Employee's job trust	1	6.7	Braganza et al. 2021
Moderator			
Adoption of AI	1	6.7	Braganza et al. 2021
METHOD			
Research approach			
Conceptual	11	73.3	Du and Xie 2020; Murtarelli 2021. Novak 2020
Qualitative	1	6.7	Stahl et al. 2021
Quantitative	2	13.7	Ferreira 2020; Braganza et al. 2021
Mixed-methods	1	6.7	Loureiro et al. 2020
Research method			
Conceptual framework development	10	66.7	Du and Xie 2020; Murtarelli 2021. Novak 2020
Literature review	2	13.3	Di Vaio et al. 2020; Loureiro et al. 2020
AI-based method (ML)	1	6.7	Ferreira et al. 2020
Survey	1	6.7	Braganza et al. 2020
Case Study	1	6.7	Stahl et al. 2021
Analysis			
PLS-SEM	1	6.7	Braganza et al. 2020
ML and Agglomerative Hierarchical Clustering	1	6.7	Ferreira 2020
Bibliografic analysis	1	6.7	Loureiro et al. 2020
Topic modeling	1	6.7	Loureiro et al. 2021
Comparative analysis	1	6.7	Stahl et al. 2021
Type of data			
Declarative	1	6.7	Braganza et al. 2020
Secondary	2	13.3	Stahl et al. 2021; Ferreira 2020

Other (articles for conceptual papers)	12	80.0	Du and Xie 2020; Murtarelli 2021. Novak 2020
TOT	**15**	**100**	

Note: the percentages are calculated over the total number of papers in the cluster (15)

4.3.1. Ethical Approaches to AI in Marketing Research

The papers in this cluster mainly focus on issues related to consumer decision-making, privacy, trust and AI technology adoption. In this regard, Stahl et al. (2021) conduct an ethical impact analysis of AI through a multidimensional study comprising 10 case studies and five scenarios. The authors suggest that the technical and economic benefits of AI are counterbalanced by legal, social and ethical issues. In particular, the AI ethics literature is divided into three streams: (1) specific issues related to the application of machine learning, particularly those related to the transparency of algorithms, the risks of biases and discrimination, and data security; (2) social and political questions arising in a digitally enabled society, such as those regarding human replacement, power asymmetries, the distribution of benefits and warfare; and (3) metaphysical questions about the nature of reality and humanity, such as those regarding the emergence of cyborgs and transhumans. Similarly, Du and Xie (2020) conduct a multilayered ethical analysis of AI products at the product, consumer, and society levels. These authors identify ethical issues at each level and propose socially responsible actions that companies can implement in the domain of AI.

4.3.2. Ethics of AI at the Product Level

At the product level, due to the increased capacity of machines to elaborate data, biased information processing might generate unfairness and unethical behavior. On the one hand, machines are often thought to be more objective and less prone to biases than human beings; on the other hand, there has been evidence of AI biases that directly affect the quality of AI-enabled products and user satisfaction. At the product level, the ethical design of machines also plays an important role (Du and Xie 2020). Ethical AI design refers to the integration of ethical principles into AI-enabled products to ensure a proper alignment of the ethical values of the products and their users, which is critical for developing consumer trust. In this regard, the necessity of defining ethical guidelines for AI products has been highlighted by many researchers in different contexts, from autonomous vehicles (Novak 2020) to chatbots (Murtarelli et al. 2021).

4.3.3. Ethics of AI at the Consumer Level

Privacy and cybersecurity are the main issues at the consumer level. Privacy issues have increasingly attracted academics' attention, and they have multiple dimensions, including information collection, unauthorized information use, and improper information access by third parties (Davenport et al. 2020; Malhotra et al. 2004; Smith et al. 1996; Thomaz et al. 2020; Wirtz et al. 2018). According to Murtarelli et al. (2021), the collection of personal and impersonal data linked to individual behaviors within the digital marketplace is made possible by technology, which raises concerns about information privacy, data protection, a lack of control over personal data and potential slavery to technological devices. These issues should be addressed through the application of numerous measures that ensure information confidentiality, integrity and availability (Murtarelli et al. 2021).

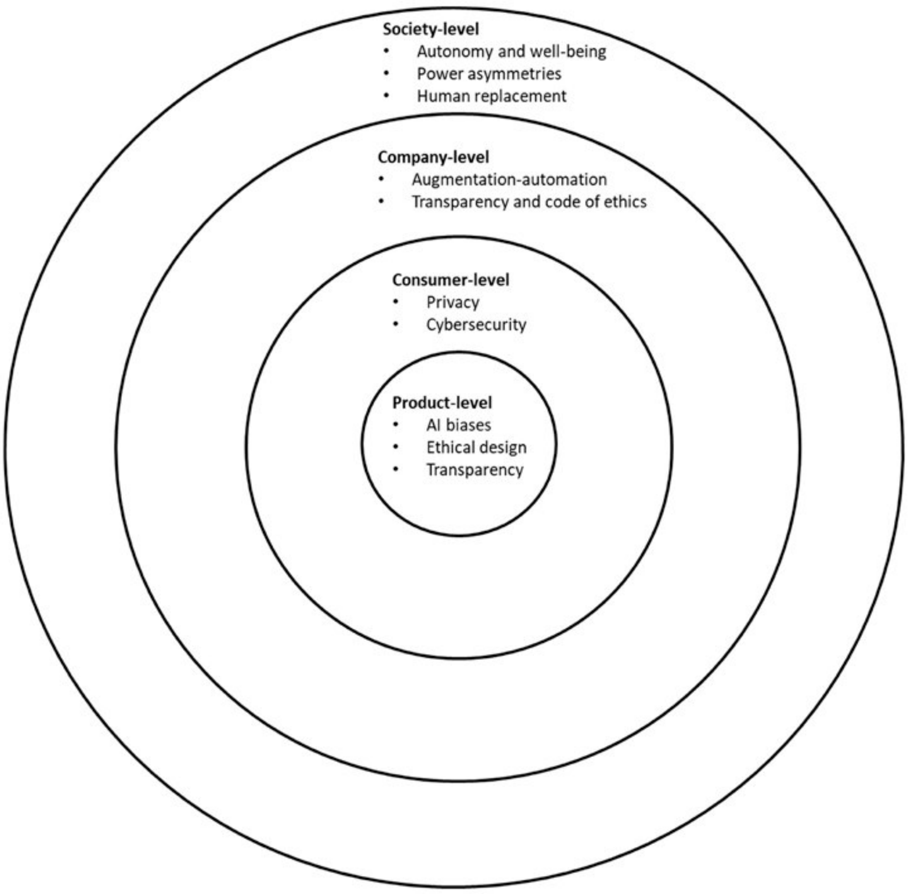
4.3.4. Ethics of AI at the Societal Level

At the societal level, Du and Xie (2020) discuss issues such as autonomy, well-being, and job replacement. Relatedly, Banker and Khetani (2019) suggest that citizens frequently depend too much on algorithm-generated recommendations and that this poses potential harm to their own well-being and leads them to play a role in propagating systemic biases that can influence other users. In addition, citizens might have different levels of access to data and AI technologies, which introduces the risk of power asymmetries (Murtarelli et al. 2021). In this regard, Letheren et al. (2020) imagine a dystopic, utopic and "dualopian" future of society due to AI. On the one hand, the pessimistic dystopic dimension of this view stems from the increasing anxiety related to AI and robotics, highlighting their risks; on the other hand, the utopic dimension of this view counterbalances this anxiety and mistrust with its vision of a transformative AI, which will improve society through its benefits. Finally, the authors discuss what they suspect will be the reality: AI will be a form of gray or 'shapeshifting' magic (Letheren et al. 2020 p. 5). This technology and its consequences on society will change depending on the circumstances and relevant influences, potentially producing positive or negative outcomes and engendering both benefits and risks.

4.3.5. Ethics of AI at the Company Level

In addition to investigating AI at the societal, consumer and product levels, researchers have started to point out the need to address AI and technology-related ethical issues at the company level. For instance, Vargo and Lusch (2016) suggest the need to effectively address technology-related ethical challenges, particularly those concerning the growing application of AI in business environments. In fact, the authors suggest that this provides opportunities for companies to develop core competences in the emerging field of AI, enhancing the relationships between firms and central actors in the service ecosystem and society (Du and Xie 2020; Vargo and Lush 2016). Vallaster et al. (2019) point out the need to investigate the conditions that enable entrepreneurs and organizations to implement new AI technologies that might involve questionable ethical practices. The authors suggest that to function properly, companies need to define a code of ethics and be transparent in terms of how they use AI applications. For instance, companies should clarify how they use consumer data and build algorithms to predict consumer behaviors (Fernandez-Rovira et al. 2021). In addition, Makarius et al. (2020) investigate the ways in which employees and AI can collaborate to establish different levels of sociotechnical capital. These authors suggest that the effective socialization and integration of AI allows organizations to rise with machines rather than against them; this includes adopting, adapting and assimilating these technologies while ensuring that ethical and legal boundaries are not crossed. In this regard, Huang and Rust (2018) suggest that augmentation-automation duality should be considered when deciding which tasks should be delegated to AI and which tasks should be done by employees alone. In the same vein, Davenport et al. (2020) and Guha et al. (2021) suggest that AI will be more effective if it augments humans rather than replacing them. Thus, as shown in Figure 7, we propose that a company-level layer should be integrated into Du and Xie's (2020) categorization of the ethical challenges of AI.

Figure 7 Ethical challenges of AI (Adapted from Xu and Die 2020)



4.4. Cluster 4: Consumer Behaviors and Psychology in the Era of AI

In this cluster, we review 26 papers following the TCCM protocol. Nineteen percent of these papers investigate consumers' decision-making when they use and interact with AI by applying Theories of Choice Architecture (Kahneman and Tversky 2014). In contrast, 11.5 % of the papers apply Stimulus-Organism-Response Theory (Mehrabian and Russell 1974). In addition, the papers in this cluster tend to investigate the psychological factors that drive AI adoption by applying Behavioral Reasoning Theory (Ajzen 1991) and Technology Adoption Models (TAM, Davis 1989; TRAM, Parasuraman 2000). Other theories refer to psychological concepts such as self-efficacy (Bandura 1986), self-construal (Trope and Liberman 2010), psychological power (Anderson and Galinsky 2006), subjective well-being (Diener 1999; Diener and Chan 2011) and self-determination (Ryan and Deci 2000). Many of the papers in this category investigate consumer behaviors online (e.g. Banker and Khetani 2019; Perez-Vega et al. 2021; Smith 2020) and in contexts such as healthcare (e.g. Dai and Singh 2020; Longoni and Cian 2020; Mele et al. 2021), food and beverage services (e.g. Longoni and Cian 2020; Mele et al. 2021; Weihrauch and Huang 2021) and transportation services, particularly those involving autonomous cars (Huang and Qian 2021; Mele et al. 2021). These papers mainly adopt traditional quantitative approaches (61.5%), which primarily feature experimental designs (38.8%, e.g. Longoni and Cian, 2020; Tassiello et al. 2021; Weihrauch and Huang 2021) and surveys (26.9%, e.g. Brill et al. 2019; Pillai et al. 2020; Smith, 2020), and they exhibit a preference for declarative data (65.5%). Moreover, 30.8% of the papers conduct studies in the United States, again highlighting a preference for conducting research in this country.

Next, we describe this cluster according to its recurrent research topics: 1) the intention to use and adopt AI, 2) consumer decision-making, and 3) consumer engagement and satisfaction.

Table 7 TCCM for cluster 4

	No. of studies	%	Exemplary studies
THEORIES			
Choice Architecture (Kahneman and Tversky, 2014)	5	19.2	Banker and Khetani 2019; Klaus and Zaichkowsky 2020; Steckel et al. 2005
Stimulus-Organism-Response Theory (Mehrabian and Russell 1974)	3	11.5	Gäthke 2020; Perez-Vega et al. 2021; Rodgers et al. 2021
Behavioral Reasoning Theory (BRT) (Ajzen 1991)	2	7.7	Huang and Qian 2021; Lalicic and Weismayer 2021
Technology Adoption Models (TAM, Davis 1989; TRAM, Parasuraman, 2000)	2	7.7	Butt et al. 2021; Pillai et al. 2020
Service-Dominant (S-D) Logic (Lusch and Vargo 2014)	2	7.7	Lalicic and Weismayer 2021; Mele et al. 2021
Self-Efficacy Theory (Bandura 1986)	1	3.8	Weihrauch and Huang 2021
Construal Level Theory (Trope and Liberman 2010)	1	3.8	Hamilton et al. 2021
Social Comparison Theory (Kruger and Dunning 1999)	1	3.8	Longoni et al. 2019
Theory of Psychological Power (Anderson and Galinsky 2006)	1	3.8	Tassiello et al. 2021
Self-Determination Theory (Ryan and Deci 2000)	1	3.8	Dellaert et al. 2020
Social Cognition Theory (Abramova and Slors 2019)	1	3.8	Poushneh 2021
Other theories (e.g. Artificial Creativity, Expectation-Confirmation theory; Hedonic versus Utilitarian Consumption)	7	26.9	Dai and Singh 2020; Longoni and Cian, 2020; Tigre Moura and Maw, 2021
No driving theory	3	11.5	
TOT	**26**	**100**	
CONTEXT			
Industry			
Online shopping	8	30.8	Perez Vega et al. 2021; Banker and Khetani 2019; Smith 2020
Offline shopping	3	11.5	Rodgers et al. 2021; Pillai et al. 2021; Hamilton et al. 2021
Digital assistant for daily activities	4	15.4	Brill et al. 2019; Poushneh 2021a,b
Health services	4	15.4	Dai and Signth 2020; Longoni et al. 2019; Mele et al. 2019
Food and beverage	3	11.5	Longoni and Cian 2020; Mele et al. 2021; Weihrauch and Huang 2021
Transportation	2	7.7	Huang and Qian 2021; Mele et al. 2021
Art and culture	2	7.7	Butt et al. 2021 ; Tigre Moura and Maw 2021
Touristic services	1	3.8	Lalicic and Weismayer 2021
Industry not explicitly stated	2	7.7	Hollebeek et al. 2020; Klaus and Zaichkowsky 2020
Country			

United States	8	30.8	Longoni et al. 2020; Longoni and Cian 2020; Weihrauch and Huang 2020
Germany	2	7.7	Tigre Moura and Maw 2021; Gäthke 2020
Austria	1	3.8	Lalicic and Weismayer 2020
China	3	11.5	Butt et al. 2021; Huang and Qian 2021; Rodgers et al., 2021
India	1	3.8	Pillai et al. 2020
Not specified	11	42.3	de Bellis and Venkataramani Johar, 2020; Dellaert et al. 2020; Hollebeek et al. 2020
TOT	**26**	**100**	
CONTEXT VARIABLES			
Independent			
Agent identity (e.g. human versus AI)	5	19.2	Longoni et al. 2019; Longoni and Cian 2020; Tigre Moura and Maw 2021
Perceived ease of use; usefulness; enjoyment	2	7.7	Butt et al. 2021 ; Pillai et al. 2020
Personality traits	2	7.7	Pillai et al. 2020; Poushneh 2021;
Perceived control	2	7.7	Poushneh 2021a, b
Consumer values	2	7.7	Lalicic and Weismayer 2021; Longoni and Cian 2020
Gender	1	3.8	Borau et al. 2021
Innovativeness	1	3.8	Pillai et al. 2020
Expectations	1	3.8	Brill et al. 2020
Dependent			
Behavioral intentions (e.g. purchase, usage, adoption)	8	30.8	Butt et al. 2020; Huang and Qian 2020; Lalicic and Weismayer 2020
Consumer choice	3	11.5	Banker and Khetani 2019; Rodgers et al. 2020; Weihrauch and Huang 2021
Attitudes towards AI (positive and negative)	2	7.7	Huang and Qian 2021; Tigre Moura and Maw 2021
Consumer satisfaction	3	11.5	Brill et al. 2020; Gäthke 2020; Poushneh 2021
Psychological power	2	7.7	Tassiello et al. 2021
Need for uniqueness	1	3.8	Longoni and Cian 2020
Resistance to AI	1	3.8	Longoni et al. 2019
Mediating			
Uniqueness neglet	1	3.8	Longoni et al. 2019
Perceived competence	1	3.8	Longoni et Cian 2020
Complexity reduction	1	3.8	Gäthke 2020
Psychological power	1	3.8	Tassiello et al. 2021
Moderating			
AI role, personalization, uniqueness, agent identity, consumer goals	1	3.8	Longoni et al. 2019
Self-efficacy	1	3.8	Weihrauch and Huang 2021
Trust, privacy concerns	1	3.8	Brill et al. 2019

Others (surprise; behavioral control; personality traits	3	11.5	Gäthke 2020; Huang and Qian 2021; Poushneh 2021
METHOD			
Research approach			
Conceptual	8	30.8	de Bellis and Venkataramani Johar 2020; Hamilton et al. 2021; Hollebeek et al. 2021
Qualitative	1	3.8	Mele et al. 2021
Quantitative	16	61.5	Lalicic and Weismayer 2021; Longoni and Cian 2021; Weihrauch and Huang 2021
Research method			
Conceptual framework development	8	30.8	de Bellis and Venkataramani Johar, 2020; Hamilton et al. 2021; Perez-Vega et al. 2021
Literature review	1	3.8	Klaus and Zaichkowsky 2020
Case study	1	3.8	Mele et al. 2021
Survey	7	26.9	Brill et al. 2020; Pillai et al. 2020; Smith 2020
Experimental design	10	38.5	Longoni and Cian 2021; Tassiello et al. 2021; Weihrauch and Huang 2021
Field study	2	7.7	Longoni and Cian 2021; Longoni et al. 2019
Analysis			
Anova, Mavona, Ancova	10	38.5	Longoni and Cian 2021; Tassiello et al. 2021; Weihrauch and Huang 2021
PLS-SEM, SEM	3	11.5	Brill et al. 2020; Pillai et al. 2020; Rodgers et al. 2021
Regression, Mediation-Moderation	5	19.2	Butt et al. 2020; Gäthke 2020; Huang and Qian 2021
Fuzzyset qualitative comparative analysis	1	3.8	Lalicic and Weismayer 2020
Other (procedure of conceptual contributions, MacInnis's 2011; selective coding, Scott and Howell, 2008).	7	26.9	Dellaert et al. 2020; Klaus and Zaichkowsky 2020; Mele et al. 2021
Type of data			
Declarative	17	65.4	Brill et al. 2020; Pillai et al. 2020; Smith 2020
Secondary data	1	3.8	Mele et al. 2020
Other (articles for conceptual papers)	8		De Bellis et al. 2020 ; Hamilton et al. 2021; Hollebeek et al. 2021
TOT	**26**	**100**	

Note: concerning the theoretical framework, some papers belong to more categories (Dellaert et al. 2020). Concerning the industry, some papers belong to more categories (Longoni and Cian 2021; Longoni et al. 2019; Tigre Moura Maw 2021). Concerning the methodology, some papers belong to more categories (Mele et al. 2020; Longoni and Cian 2020). The percentages are calculated over the total number of papers in the cluster (26)

4.4.1. Intention to Use and Adopt AI

A vast stream of research has investigated AI adoption and usage intentions through the lens of well-established theories such as the Theory of Reasoned Action and the Theory of Planned Behavior (Ajzen 1991), Technology Acceptance Models (Davis 1989; Venkatesh 2000; Venkatesh et al. 2011), Innovation Diffusion Theory (Rogers 1995), and Technology Readiness Theory (Parasuraman 2000). Thus, researchers have begun identifying the antecedents and consequences of AI usage and adoption in many different contexts, ranging from retail stores (Pillai et al. 2020) and shopping systems (de Bellis and Venkataramani Johar 2020) to gaming environments (Butt et al. 2021) and artistic and musical experiences (Tigre Moura and Maw 2021), including the adoption and usage of new AI products such as autonomous vehicles (Eggers and Eggers 2021; Huang and Qian 2021)

In the context of AI-powered automated retail stores, Pillai et al. (2020) investigate shopping intentions, integrating the technology readiness and acceptance model with AI-specific constructs. The authors identify the antecedents of consumers' shopping intentions in AI-powered automated stores, specifically exploring perceived ease of use, perceived usefulness, perceived enjoyment, customization and interactivity. Additionally, de Bellis and Venkataramani Johar (2020) investigate autonomous shopping systems, attempting to identify and overcome barriers to consumer adoption in this context. On the one hand, the authors suggest that the functional benefits of these systems are evident; on the other hand, they raise concerns regarding psychological consumption motives and ingrained human–machine relationships stemming from the delegation of decisions and tasks to technology. Building on innovation diffusion theory and the technology acceptance model and flow theory, Butt et al. (2021) investigate AI tools in the context of the gaming industry. Additionally, in this study, the authors focus on how the utilitarian aspects of this technology - such as its perceived easiness and usefulness and its advantages - and its hedonic aspects - such as those related to enjoyment, customization, and interactivity - shape gamers' intentions to play with AI-powered avatars. The authors highlight that due to their newly implemented functionalities, these tools have enhanced consumer experiences.

On the one hand, some contexts, such as gaming, favor extensive AI usage and adoption (Butt et al. 2021); on the other hand, there are many psychological roadblocks that limit the adoption of AI in other contexts. For instance, Tigre Moura and Maw (2021) investigate listeners' perceptions of music composed by AI, showing that consumers have rather negative perceptions of and low purchase intentions toward AI music and that they have negative credibility perceptions of musicians who use AI. Thus, consumers seem to be less keen to accept and use AI in contexts that require a high level of human-like intelligence, such as creativity or emotional intelligence.

According to Longoni and Cian (2020), preferences regarding and resistance to AI also depend on the utilitarian/hedonic attribute trade-offs within the contexts where the technology is used. In particular, consumers seem to believe that AI recommenders are more competent than human recommenders in utilitarian contexts and less competent than human recommenders in hedonic contexts. As a consequence, when utilitarian attributes are more important to consumers, they tend to prefer AI recommenders over human recommenders. However, when hedonic attributes are more important, consumers seem to resist AI recommendations and prefer human ones.

In addition to contextual issues, researchers have started to investigate the acceptance of new disruptive technological products that use AI. For instance, autonomous vehicles (AVs) have increasingly drawn academic interest, as they might entail numerous benefits and opportunities for research and society. However, the risk associated with this technology seems to also raise concerns about its adoption (Shariff et al. 2017). In this context, Huang and Qian (2021) examine the effect of consumers' reasoning processes on their attitudes and intentions toward adopting AVs and how their psychological traits moderate these relationships. The authors show that the need for uniqueness, as a psychological trait, strengthens the association between consumers' positive reasoning regarding AVs and their adoption intentions, while the risk aversion trait intensifies the negative relationships between consumers' negative reasoning regarding AVs and their attitudes/adoption intentions.

4.4.2. Consumer Decision-Making

The research in this cluster also focuses on investigating how consumers' decision-making changes when they use and interact with AI technology. In this regard, Klaus and Zaichkowsky (2020) review the current consumer decision-making literature and theories to demonstrate consumers' increasing tendency to outsource decisions to AI. In fact, AI increases the convenience of consumers, as they outsource their decisions to bots and algorithms, especially those related to low-involvement everyday purchases (Klaus and Zaichkowsky 2020). Additionally, Dellaert et al. (2020) investigate consumers' decision-making within bot interactions. In particular, the authors propose that users may be more susceptible to being influenced in terms of their choices by voice-based assistants perceived to be warm due to strong human-like cues such as gender, tone of voice and competence due to their provision of immediate answers and real-time information. Tassiello et al. (2021) investigates consumer–voice assistant (VA) interactions in the context of food and beverage purchase choices and the role that psychological power plays in the consumer decision-making process of this setting. The authors suggest that both involvement and the psychological condition of power meditate consumers' willingness to purchase. Consistent with Klaus and Zaichkowsky (2020), this study shows that consumers are more likely to purchase low-involvement products than high-involvement products through bots, particularly when experiencing high-power states. The consumer decision-making process has also been investigated in relation to the degree of interactivity within the surrounding environment. In this regard, Steckel et al. (2005) argue that the nature of the interactive environment chosen by a customer has a significant impact on the customer's behavior and decision-making process. When they have online help, consumers make better choices. However, "help" functions are sometimes difficult to implement. In addition, companies have to induce customers to use a help function. In addition to the main challenges related to implementing an interactive environment, the authors mention the need to develop tools for real-time personalization and decision-making regarding how much information to provide and when, where and how to involve customers (Steckel et al. 2005).

Being influenced by algorithms in the decision-making process can also engender negative consequences for consumers. In this regard, Banker and Khetani (2019) investigate algorithm overdependence, which refers to situations in which consumers frequently depend too heavily on algorithm-generated recommendations. Algorithm overdependence poses potential harm to consumers' well-being. In addition, it leads consumers to play a role in propagating systemic biases that can influence other users. Thus, on the one hand, a stream of research points out that consumers tend to be averse to algorithmic forecasting even when it is superior to human forecasting (Dietvorst et al. 2015); on the other hand, there is evidence that individuals might also rely too much on algorithmic decision-making due to their belief that algorithms have greater domain expertise than humans (Banker and Khetani 2019).

4.4.3. Consumer Engagement and Satisfaction

The last subtopics of the cluster refer to consumer engagement and customer satisfaction. Hollebeek et al. (2021) investigate consumer engagement in automated service encounters. The authors propose that as AI initially automates relatively routine, functional tasks, robotic-based service interactions should generate fairly low levels of brand engagement. In addition, consumer engagement in robotic process automation-based interactions might decline over time. However, consistent with Huang and Rust (2021), these authors expect the performance of machine learning applications to differ across transactional (vs. relational) interactions. In transactional interactions, customers focus on functional exchange benefits (Hollebeek et al. 2021). As machine learning algorithms can facilitate user decision-making, for instance, by providing relevant information, the authors suggest that customers should positively engage with brands through transactional machine learning-based interactions. In contrast, relational interactions are characterized by customers' desire to bond or identify with brands. In this case, machine learning could diminish brand engagement, as it offers monotonous, impersonalized interactions. Concerning deep learning, the authors suggest that customers' brand engagement through effective deep learning-based services should become more similar to consumer engagement in equivalent human-to-human interactions over time due to the increasing ability of this technology to simulate human intelligence. Additionally, Perez-Vega et al. (2021) investigate how firms can solicit online customer engagement behaviors through the use of information processing systems enabled by AI. In addition, consumer satisfaction has been investigated in relation to AI technology. In this regard, Brill et al. (2019) suggest that there is little empirical evidence of customer satisfaction with AI technologies such as digital assistants. However, the authors show that customer expectations and the confirmation of such expectations are positively and significantly related to customer satisfaction with AI technologies, providing evidence that customer expectations are satisfied through digital assistant interactions, at least in the case of successful interactions. Additionally, Gäthke (2020) suggests that AI applications in augmented reality apps used in service settings tend to improve customer satisfaction and loyalty.

4.5. Cluster 5: AI, Company Transformation and Strategy

During recent decades, companies have witnessed strong development in the context of digital technologies. In particular, AI and algorithms are increasingly affecting both production systems and business strategies (Bertani et al. 2021). In this regard, the papers in this cluster offer insights into the way companies are adapting to AI and integrating it into their businesses. We review 41 papers following the TCCM protocol (Table 8). Job Automation Theory (Huang and Rust 2018), the SD-Logic Framework (Lusch and Vargo 2014) and Value Creation and Cocreation Theories (Grönroos and Voima 2013) are among the most commonly used theoretical frameworks in this cluster. In contrast to the previous cluster, we find a substantial number of papers that focus on B2B settings (Battisti and Brem 2020; Bonnin and Alfonso 2019; Leone et al. 2021). The United States is the most frequently investigated country in this cluster (de Ruyter et al. 2020; Leone et al. 2021; Luo et al. 2021). Moreover, 63% of the papers are conceptual, while 22% adopt a qualitative approach; additionally, 14.6% of the papers use case studies (Allal-Chérif et al. 2021; Battisti and Brem 2020; Leone et al. 2021). Finally, 14.6% of the papers use secondary data such as companies' financial reports (Leone et al. 2020; Allal-Chérif et al. 2021; Fossen and Sorgner, 2021; Leone et al. 2020). In the next section, we describe this cluster in terms of its most recurrent research subtopics: 1) company decision-making augmented by AI, 2) business model adaptation and digitalization, and 3) AI, marketing and service strategies.

Table 8 TCCM for cluster 5

	No. of studies	**%**	**Exemplary studies**
THEORIES			
Job Automation Theory and Multiple Level of Intelligence (Huang and Rust 2018)	6	14.6	Davenport et al. 2020; Huang and Rust 2021b; Rust 2020;
SD Logic (Lusch and Vargo 2014)	5	12.2	Langley et al. 2021; Rust 2020; Tong et al. 2020

Value Creation and Co-Creation (Grönroos & Voima, 2013)	4	9.8	Battisti and Brem 2020; Leone et al. 2021; Sjödin et al. 2020
Decision-Making Theories (Kahneman and Tversky 2014)	3	7.3	Allal-Chérif et al. 2021; Krabuanrat and Phelps 1998; Shrestha et al. 2021
Personalization (McCarthy 1960)	2	4.9	Tong et al. 2020; Rust 2020
Agent-Based Models (ABM) (Gallegati, 2018)	2	4.9	Bertani et al. 2021; Rust 2020
Business-Model Innovation Theories (Adner 2017)	2	4.9	Burström et al. 2021; Langley et al. 2021
Information Processing Theory (Newell and Simon 1972)	2	4.9	Luo et al. 2021; Meyer et al. 2020
Narrative Theory (Bruner 1987)	1	2.4	Bonnin and Alfonso 2019
Occupational Choice Theories (Lucas 1978)	1	2.4	Fossen and Sorgner 2021
Socio-Technical Systems Theory (Resnick 2001)	1	2.4	Makarius et al. 2020
Entrepreneurship Theory (Foss 2007)	1	2.4	Ehret and Wirtz 2017
Assemblage Theory (Hoffman and Novak 2018)	1	2.4	Mithas et al. 2020
No driving theories	13	31.7	de Ruyter et al. 2020; Guha et al. 2021; Kozinets and Gretzel 2021; Rampersad 2020; Sohrabpour et al. 2021
TOT	**41**	**100**	
CONTEXT			
Industry			
B2B	6	14.6	Battisti and Brem 2020; Bonnin and Alfonso 2019; Leone et al. 2021
B2C:			
Offline shopping	1	2.4	Luo et al. 2021
Healthcare	1	2.4	de Ruyter et al. 2020
Professional services	1	2.4	Sampson 2021
Food and beverage	1	2.4	Sohrabpour et al. 2021
Technology	3	7.3	Allal-Chérif et al. 2021; Bertani et al. 2021; Fossen et Sorgner 2021
Manufacturing	2	4.9	Burström et al. 2021; Krabuanrat and Phelps 1998
Education	1	2.4	Rampersad 2020
Organizations	2	4.9	Langley et al. 2021; Makarius et al. 2020
Not specified	23	56.1	Huang and Rust 2021b; Tong et al. 2020; Yadav and Pavlou 2020
Country			
United States	6	14.6	Luo et al. 2021; Leone et al. 2021; de Ruyter et al. 2020
Sweden	3	7.3	Burström et al. 2021; Pemer 2020; Sjödin et al. 2020
Italy, Germany, Finland	1	2.4	Battisti and Brem 2020
France	1	2.4	Bonnin and Alfonso 2019
UK	1	2.4	Krabuanrat et al. 2020
Middle East	1	2.4	Sohrabpour et al. 2021
Australia	1	2.4	Rampersad 2020
Thailand	1	2.4	Krabuanrat et al. 2020

Not specified	3	73.2	
TOT	4	100	
CHARACTERISTICS VARIABLES			
Independent			
AI applications	2	4.9	Allal-Chérif et al. 2021; Guha 2021
Digitalization	1	2.4	Fossen et Sorgner 2021
Problem solving, critical thinking, communication and	1	2.4	Rampersad 2020
Business analytics, cloud computing, collaborative	1	2.4	de Ruyter et al. 2020
platform Exchange rate; advertising; costs; discount; price	1	2.4	Sohrabpour et al. 2020
Dependent			
Company performance and sales	3	7.3	Allal-Chérif et al. 2021; de Ruyter et al. 2020; Sohrabpour et al.
Employee performance	1	2.4	2020 Luo et al. 2021
Entrepreneurship	1	2.4	Fossen et Sorgner 2021
Innovation	1	2.4	Rampersad 2020
AI adoption	1	2.4	Guha 2021
Cloud computing service and collaboration platforms	1	2.4	De Ruyter et al. 2020
Mediating			
Mistakes and learning	1	2.4	Luo et al. 2021
Moderating			
Agent identity (human versus AI)	1	2.4	Luo et al. 2021
Application value; online versus in line store; ethics concerns	1	2.4	Guha et al. 2021
METHOD			
Research approach			
Conceptual	2 6	63.4	Haenlein and Kaplan 2020; Kozinets and Gretzel 2021; Rust 2020
Qualitative		22.0	Guha 2021; Makarius et al. 2020 ; 2020
Quantitative	6	14.6	Bertano et al. 2021; Fossen et Sorgner 2021; Rampersad 2021
Research method			
Conceptual framework	1 7	41.5	Rust 2020; Haenlein and Kaplan 2021; Kozinets and Gretzel 2021
develeopment		22.0	Singh et al. 2021; Yadav and Pavlou 2020; Zhang et al. 2020
AI-based method (Genetic Programming)	1	2.4	Sohrabpour et al. 2021
Case Studies	6	14.6	Allal-Chérif et al. 2021; Battisti and Brem 2020 ; Leone et al; 2021
Survey	1	2.4	Rampersad et al. 2020
Field study	2	4.9	De Ruyter 2021; Fossen et Sorgner
Experiments	2		Bertani et al. 2021; Luo et al. 2021
Interviews	3		Guha et al. 2021; Krabuanrat and Phelps 1998; Pemer 2020
Analysis			

Data triangulation analysis	3	7.3	Allal-Chérif et al. 2021; Battisti and Brem 2020; Leone et al. 2021
Content analysis	2	4.9	Bonnin and Alfonso 2019; Pemer 2020
Thematic analysis	2	4.9	Burström et al. 2021; Sjödin et al. 2020
Structural narrative analysis	1	2.4	Bonnin and Alfonso 2019
Cost-benefit analysis	1	2.4	Bertani et al. 2021
Regression analysis and SEM	2	4.9	Luo et al. 2021 ; Rampersad et al. 2020;
Multivariate analysis	1	2.4	Fossen et Sorgner 2021
Vignette approach	1	2.4	Langley et al. 2021
Bibliometric analysis	1	2.4	Zhang et al. 2020
Predictive modeling	1	2.4	de Ruyter et al. 2020
Genetic programming	1	2.4	Sohrabpour et al. 2020
Type of data			
Declarative	12	29.3	Bertani et al. 2021; Luo et al. 2021; Rampersad et al. 2020
Behavioral	1	2.4	Luo et al. 2021
Secondary data	6	14.6	Allal-Chérif et al. 2021; Fossen and Sorgner 2021; Leone et al. 2021
Other (articles for conceptual papers)	26	63.4	Kaplan and Haenlein 2019; Kozinets and Gretzel 2021; Rust 2020
TOT	**41**	**100**	

Note: concerning the theory, some papers belong to more categories (Mithas et al. 2020; Rust 2021). Concerning the country, some papers belong to more categories (Battisti et al. 2020). Also, some papers uses both primary and secondary data (Bonnin and Alfonso 2020; Battisti et al. 2020). The percentages are calculated over the total number of papers in the cluster (41)

4.5.1. Company Decision-Making Augmented by AI

Shrestha et al. (2021) conceptualize decision-making processes augmented by deep learning algorithms as deep learning–augmented decision-making (DLADM) processes. These authors suggest some current applications of DLADM in the context of company strategy, such as its use for targeting consumers, monitoring trends, forecasting and developing prognostic systems for scheduling, resource allocation, and manufacturing planning. These applications are playing an increasingly important role in facilitating and assisting companies' decision-making (Grewal et al. 2017). In addition, thanks to its ability to increase efficiency, connectivity and data harvesting, AI technology has the potential to increase businesses' profitability (Grewal et al. 2017) and to improve company performance through improved supplier relationship management policies and interdepartmental collaborations (Allal-Chérif et al. 2021). AI-augmented company decision-making has also been investigated in the context of the service industry. In this regard, Meyer et al. (2020) propose a framework that illuminates and informs strategic choices regarding service automation, including the use of AI in professional services. Their framework considers service automation decisions as a matter of knowledge management and, in particular, as a choice between human resources and codified knowledge assets.

4.5.2. Business Model Adaptation and Digitalization

Companies have started to adapt their business models to better develop and implement AI technology (Davenport et al. 2020). In this regard, researchers have started to investigate business model adaptation to AI (Burström et al. 2021; Ehret and Wirtz 2017; Langley et al. 2021). For instance, Burström et al. (2021) suggest that AI business model innovation should be aligned with ecosystem innovation such that organizational microelements are connected with ecosystem macro dimensions. Aside from the new opportunities of smart technologies, Ehret and Wirtz (2017) suggest that AI might pose a threat to companies that are not able to address its challenges within their existing business models. Thus, the authors identify and propose three business models to adapt to AI: 1) manufacturing asset acquisition, maintenance, repair, and operation; (2) the use of innovative information and analytical services for manufacturing (e.g., based on AI, big data, and analytics) and (3) the development of new services targeted at end users that feature efficient customization.

Additionally, companies must understand how to design business models to adapt jobs to AI and digitalization (Fernandez-Rovira et al. 2021; Fossen and Sorgner 2021; Pemer 2020). In this regard, Sampson (2021) empirically tests a model for the automation of professional services. This author suggests that companies should implement different degrees of automation based on the tasks at hand. In particular, some tasks should be only augmented by automation, as they still require the skills of professionally trained workers. Other tasks, which can be deskilled by automation, should instead be transferred to lower-cost workers, while others should be directly executed by customers through self-service technologies. Researchers have also investigated the ways in which employees and AI can collaborate to generate different levels of sociotechnical capital (Makarius et al. 2020). In this regard, Makarius et al. (2020) highlight the importance of AI socialization in the context of successfully integrating intelligent systems and employees. Pemer (2020) suggests that the fit between technological innovation and the type of intelligence that services built on, as well as the occupational identities and service climate within a firm, substantially contribute to the way companies embrace digitalization. Sjödin et al. (2020) suggest that agile microservice innovation approaches help foster value cocreation in digital servitization. In addition, according to Luo et al. (2021), AI offers an opportunity for companies to train sales agents through AI coaches.

4.5.3. AI, Marketing and Service Strategies

In addition to inducing an adaption of company business models, AI can strongly affect the way companies define their short- and long-term strategies. In the realm of marketing, Huang and Rust (2021a) suggest that AI can provide potential benefits in relation to defining marketing strategies. In particular, marketers can use mechanical AI for segmentation, thinking AI for targeting, and feeling AI for positioning. Regarding the implementation of marketing actions, mechanical AI can be used for standardization, thinking AI for personalization, and feeling AI for relationalization. Additionally, Davenport et al. (2020) suggest that AI transforms marketing strategies due to its excellent predictive ability and accuracy. However, these authors highlight the need to better understand how these algorithms can improve forecasting demands for truly new products. In addition, concerning sales strategies, companies must learn to organize their organizational components, including their AI bots and human salespeople (Davenport et al. 2020).

Besides identifying its benefits, researchers have tried to define the risks and challenges associated with AI in terms of defining marketing strategies (De Bruyn et al. 2020; de Ruyter et al. 2020; Guha et al. 2021; Kozinets and Gretzel 2021). In this regard, Kozinets and Gretzel (2021) describe three important challenges that marketers face when they apply AI. First, although AI gives marketers unprecedented knowledge about large-scale consumer patterns, it increases the complexity of extracted insights regarding consumer behaviors. To face this challenge, marketers should continue to use irreplaceable human skills such as empathic understanding. Second, despite the increasing efficiencies and digital touchpoints that AI provides, this technology might diminish opportunities for marketer–customer contact and relationships. Finding new ways of offering a personal touch might help overcome this challenge. Third, as marketers increasingly rely on AI, they become more vulnerable to changes in algorithms. Diversifying marketing channels might be a valuable solution to address this challenge. In addition, De Bruyn et al. (2020) highlight other technological pitfalls and dangers that marketing managers need to be aware of when implementing AI in their organizations. In particular, the authors highlight the risks of badly defined objective functions, unsafe or unrealistic learning environments, biased AI, explainable AI, and controllable AI.

AI is also increasingly reshaping service strategies (de Ruyter et al. 2020). For instance, as AI-powered chatbots gradually take over routine service requests, frontline employees can focus on more complex tasks, taking on the role of advisors and engaging in cross- and upselling. In addition, the wide range of functionalities AI offers can support employees in better understanding their customers and determining which solutions to offer them. Furthermore, in combination with data on customers' personalities (e.g., IBM Watson

Personality Insights), NLP can assist service agents in adopting the most effective tone of voice during highly personalized service experiences (de Ruyter et al. 2020). However, companies also need to identify the right way to implement these technological applications and quickly adapt to the changing technological environment.

4.6. Cluster 6: AI and Social Media Management

The 11 papers belonging to this cluster mainly investigate consumer relationship management in the context of social media, such as Facebook and Instagram (54.5%), drawing on theories related to the Customer Experience Journey (Lemon and Verhoef 2016), Theories of Emotions (Cabanac 2002), Customer Engagement (Brodie et al. 2011), Social Network Analysis Theory (Muller and Peres 2019; Nitzan and Libai 2011) and E-Word-Of-Mouth (WOM) communication concepts (Hennig-Thurau et al. 2004) (Table 9). Overall, 54.5 % of these studies use AI-based methods to conduct their research and analyze their results (Chuah and Yu 2021; Pantano and Pizzi 2020; Pitt et al. 2018). In particular, 36.4% conduct social media sentiment analyses by examining text (Chuah and Yu 2021; Pitt et al. 2018; Pizzi et al. 2020; Sidaoui et al. 2020) and 18.2% employ image recognition (Capatina et al. 2020; Kaiser et al. 2020), mainly using behavioral data (36.4%) available on the net.

Table 9 TCCM for cluster 6

THEORIES	**No. of studies**	**%**	**Exemplary studies**
Customer Experience Journey (Lemon and Verhoef, 2016)	4	36.4	Hoyer et al., 2020; Libai et al., 2020; Wilson-Nash et al., 2020
Emotions Theory (Cabanac 2002)	2	18.2	Pitt et al. 2020; Sidaoui et al. 2020
Customer Engagement and Experience (Brodie et al. 2011)		9.1	Kaiser et al. 2020
Social Network Analysis Theory (Muller and Peres 2019; Nitzan and Libai 2011)	1	9.1	Libai et al . 2020
eWOM Communication (Hennig-Thurau et al. 2004)	1	9.1	Verma an d Yadav 2021
Theory of Media Effects (Gerbner and Gross 1976)	1	9.1	Dholakia and Reyes 2018

Emotional Contagion (Hatfield et al. 2014)	1	9.1	Chuah and Yu 2021
Job Automation (Huang and Rust 2018)	1	9.1	Pantano and Pizzi 2020
Types of AI Intelligence (Kaplan and Haenlein 2019)	1	9.1	Capatina et al. 2020
TOT	**11**	**100**	
CONTEXT			
Industry			
Social media (Facebook, Instagram)	6	54.5	Chuah and Yu 2021; Libai et al. 2020; Wilson-Nash et al. 2020
General digital innovations (e.g. chatbots)	4	36.4	Hoyer et al. 2020; Pantano and Pizzi,2020; Sidaoui et al. 2020
Healthcare	1	9.1	Pitt et al. 2020
Country			
United states	2	18.2	Kaiser et al. 2020; Pantano and Pizzi 2020
Germany	1	9.1	Kaiser et al. 2020
Italy, France, Romania	1	9.1	Capatina et al. 2020
UK	1	9.1	Wilson-Nash et al. 2020
Not specified	7	63.6	Dholakia and Reyes 2021; Hoyer et al. 2020; Libai et al. 2020;
TOT	**11**	**100**	
CHARACTERISTICS VARIABLES			
Independent			
Number of photos	1	9.1	Kaiser et al. 2020
Brand promotion	1	9.1	Kaiser et al. 2020
Emotional expressions	1	9.1	Chuah and Yu 2021
Customer emotions and profiles	1	9.1	Pitt et al. 2020
Dependent			
Affective reactions	3	27.3	Chuah and Yu 2020; Pitt et al. 2020; Sidaoui et al. 2020
Brand love and loyalty	1	9.1	Kaiser et al. 2020
WOM endorsement	1	9.1	Kaiser et al. 2020
Customer satisfactions	1	9.1	Pitt et al. 2020
METHOD			
Research approach			
Conceptual	4	36.4	Hoyer et al. 2020; Libai et al. 2020; Verma et al. 2020
Qualitative	1	9.1	Wilson-Nash et al. 2020
Quantitative	4	36.4	Chuah and Yu 2021; Sidaoui et al. 2020; Pantano et al. 2020
Mixed-methods	2	18.2	Capatina et al. 2020; Pitt et al. 2020;
Research method			
Conceptual framework development	3	27.3	Dholakia and Reyes 2021; Hoyer et al. 2020; Libai et al. 2020;
Literature review	1	9.1	Verma et al. 2020
AI-based method (ML, DL, Text Mining, Image Processing)	6	54.5	Chuah and Yuhu 2020; Pantano et al. 2020 ; Pitt et al. 2021;
Survey	2	18.2	Capatina et al. 2020; Kaiser et al. 2020
Experiment	1	9.1	Sidaoui et al. 2020

Interviews	1	9.1	Wilson-Nash et al. 2020
Focus group	1	9.1	Capatina et al. 2020
Analysis			
Sentiment and text analysis	4	36.4	Chuah and Yuhu 2020; Pantano et al. 2020; Pitt et al. 2021; Sidaoui et al. 2021
Image analysis	2	18.2	Capatina et al. 2020 ; Kaiser et al. 2020;
Correlation and frequency analysis	1	9.1	Kaiser et al. 2020
Weight Least Square (WLS)	1	9.1	Capatina et al. 2020
Bibliometric and scientometric	1	9.1	Verma and Yadav 2021
Interview thematic analysis	1	9.1	Wilson-Nash et al. 2020
Other analytical methods (conceptual papers)	3	27.3	Dholakia and Reyes 2021; Hoyer et al. 2020; Libai et al. 2020;
Type of data			
Declarative	3	27.3	Capatina et al. 2020; Sidaoui et al. 2020; Wilson-Nash et al. 2020
Behavioral	4	36.4	Chuah and Yuhu 2021; Kaiser et al. 2020; Pitt et al. 2021; Sidaoui et al. 2020;
Secondary data	1	9.1	Pantano and Pizzi 2020
Other (articles for conceptual papers)	3	27.3	Dholakia and Reyes 2021; Hoyer et al. 2020; Libai et al. 2020;
TOT	**11**	**100**	

Note: concerning the theory, some papers belong to more than one category (Libai et al. 2020). Concerning the country some papers belong to more than one category (Capatina et al. 2020). Concerning the methodology, some papers belong to more than one category (Capatina et al. 2020; Keiser et al. 2020; Sidaoui et al. 2021). The percentage are calculated over the total number of papers in the cluster (11)

4.6.1. Consumers Relationship Management on Social Media

AI algorithms are extremely powerful in terms of monitoring online social networks (Capatina et al. 2020). Indeed, companies and researchers are becoming increasingly able to detect and understand consumers' feelings on social media through their comments and tweets (sentiment analysis) as well as their images, photos and pictures (image analysis), which allows them to determine how content can be optimally personalized (audience analysis) (Capatina et al. 2020). In addition, thanks to access to large-scale data, companies can improve their customer acquisition, retention and prioritization by conducting social network analyses (Libai et al. 2020). In this context, the academic community has proposed many new approaches. For instance, Sidaoui et al. (2020) suggest that social media can be useful in relation to enhancing consumer research through the interplay between chatbot interviewers and sentiment analysis extraction algorithms. These authors use primary qualitative data generated via chatbot interviews, investigating the effectiveness of sentiment analysis in terms of extracting useful customer experience insights. In addition, by comparing extracted sentiment polarities with established measurement scales, they empirically validate their new research approach. Additionally, researchers have started to combine image analysis and text analysis to better predict consumers' sentiments on social media. For instance, using Instagram data, Chuah and Yu (2021) combine facial recognition algorithms and lexicon-based sentiment analysis to uncover how emotional robots influence potential consumers' affective feelings. These authors highlight the possibility of emotional contagion during human-robot interactions, suggesting that displays of emotions by technology can make a difference in human-robot interactions. They also contribute to a new methodological approach that leverages advanced analytics on social media to provide an understanding of consumers' emotional reactions. Additionally, Kaiser et al. (2020) use images to understand consumers' preferences on social media. By training a powerful hybrid machine learning algorithm that uses both genetic searching and artificial neural networks, the authors suggest a new way to predict consumers' brand love, brand loyalty, and WOM endorsement from the content of the brand photos they post on Facebook.

In addition to exploring sentiment analysis, researchers have started to investigate new ways of managing online customer interactions through automation. In this regard, by conducting a patent analysis, Pantano and Pizzi (2020) highlight the extensive innovation achieved in relation to chatbots in the field of online retailing and marketing through social media. This technological innovation primarily focuses on enhancing chatbots' ability to automatically extract insights about users from different types of data and on offering personalized service by adaptively leveraging customers' information. For instance, Wilson-

Nash et al. (2020) highlight the benefits of using social bots as novel touchpoints for customer relationship management, particularly for young target customers. In this regard, the use of social bots to interact with young adults positively affects firms' value equity and relationship equity (Wilson-Nash et al. 2020).

4.7. Cluster 7: AI, E-Commerce and Financial Services

The last cluster focuses on AI applications used in the context of financial services (66.7%) and e-commerce (33.3%) (Table 10). We review 6 papers, which mainly draw on Technology Acceptance Models (TAM, Davis 1989; UTUAT, Venkatesh et al. 2003), the SD-Logic Framework (Lusch and Vargo 2014), the Theory of Affordances (Gibson 1979), Innovation Diffusion Theory (Rogers 1995), Trust Theory (Mayer et al. 1995) and Relationship Marketing (Morgan and Hunt 1994). Fifty percent of these studies are conducted in the United States and adopt a quantitative approach, and most of them use declarative data (Manser Payne et al. 2021; Moriuchi 2019; Zhang et al. 2021).

Table 10 TCCM for cluster 7

	No. of studies	%	Exemplary studies
THEORIES			
Technology Acceptance Models (TAM, Davis 1989); UTUAT (Venkatesh et al. 2003)	3	50.0	Manser Payne et al. 2021; Moriuchi 2019; Zhang et al. 2021
SD Logic(Lusch and Vargo 2014)	2	33.3	Manser Payne et al. 2021a; 2021b
Theory of Affordances (Gibson 1979)	1	16.7	Canoto et al. 2020
Innovation Diffusion Theory (Rogers 1995)	1	16.7	Manser Payne et al. 2021a
Trust Theory (Mayer et al. 1995)	1	16.7	Zhang et al. 2021
Relationship Marketing (Morgan and Hunt 1994)	1	16.7	Steinhoff et al. 2019
CONTEXT			
Industry			
Financial services	4	66.7	Canhoto et al. 2020; Manser Payne et al. 2021a ; Zhang et al. 2021;
E-commerce	2	33.3	Moriuchi 2019; Steinhoff et al. 2021
Country			
United States	3	50.0	Manser Payne et al 2021a; Zhang et

			al. 2021; Moriuchi 2019
UK	1	16.7	Canhoto 2020
Country not specified	2	33.3	Manser Payne et al. 2021 b; Steinhoff et al. 2021
TOT	**6**	**100**	
CHARACTERISTICS VARIABLES			
Independent			
Ease of use and usefulness	2	33.3	Manser Payne et al. 2021 a; Moriuchi 2019
Perceived complexity,	1	16.7	Manser Payne et al. 2021 a
Relative advantage	1	16.7	Manser Payne et al. 2021 a
Data security and safety perceptions	1	16.7	Manser Payne et al. 2021 a
Agent expertise	1	16.7	Zhang et al. 2021
Dependent			
Safety perceptions, service satisfaction	1	16.7	Manser Payne et al. 2021 a
Trust and performance expectancy	1	16.7	Zhang et al. 2021
Intention to use	2	33.3	Zhang et al. 2021 ; Moriuchi 2019
Loyalty	1	16.7	Moriuchi 2019
Mediator			
Perceptions of AI service delivery	1	16.7	Manser Payne et al. 2021a
Engagement	1	16.7	Moriuchi 2019
Moderator			
Localization	1	16.7	Moriuchi 2019
METHODS			
Research approach			
Conceptual	2	33.3	Manser Payne et al. 2021 b; Steinhoff et al. 2021
Qualitative	1	16.7	Canhoto 2021
Quantitative	3	50.0	Manser Payne et al 2021a; Zhang et al. 2021; Moriuchi 2019
Research method			
Conceptual framework development	2	33.3	Manser Payne et al. 2021b; Steinhoff et al. 2021
Survey	2	33.3	Manser Payne et al. 2021a; Moriouchi et al. 2021
Experiment	1	16.7	Zhan et al. 2021
Case Study	1	16.7	Canhoto 2020
Analysis			
SEM and Mediation-Moderation analysis	2	33.3	Manser Payne et al. 2021 a; Moriuchi 2019
Ancova and Mancova	1	16.7	Zhan et al. 2021
Other analytical methods	3	50.0	Canhoto 2020; Manser Payne et al. 2021 b; Steinhoff et al. 2021;
Type of data			
Declarative	4	66.7	Manser Payne et al. 2021 a; Moriuchi 2019; Zhang et al. 2021
Other (articles for conceptual papers)	2	33.3	Manser Payne et al. 2021 b; Steinhoff et al. 2021
TOT	**6**	**100**	

Note: concerning the theory, some papers belong to more than 1 category (Manser Payne et al. 2021a; 2021b; Zhang et al. 2021). The percentages are calculated over the total number of papers in the cluster (6).

4.7.1. Financial Services and E-Commerce in the Era of AI

Consumers' online economic transactions involving e-commerce platforms and financial services are increasingly handled by AI algorithms, attracting the interest and concern of the academic community (Steinhoff et al. 2019) According to Steinhoff et al. (2019), online transactions have become omnichannel, personalized and anthropomorphized in nature. The increased utilization of AI digital technologies linked to customer data allows this technology to augment financial services and cocreate value with customers through market efficiencies and data assimilation (Huang and Rust 2018; Manser Payne et al. 2021a; 2021b). According to Manser Payne et al. (2021), the AI-powered financial services ecosystem consists of three primary network actors – consumers, traditional financial industry organizations such as banks, and supporting fintech institutions that use technology to improve and automate the delivery of financial services. Fintech institutions may assist traditional banks by providing AI technologies to improve their infrastructure. In addition, they may help address data security issues and detect fraudulent behavior (Manser Payne et al. 2021a). In this regard, Canhoto (2020) investigates how machine learning algorithms may assist financial services organizations in the detection and prevention of money laundering, suggesting that it is possible to use reinforced machine learning and, to an extent, unsupervised learning to model unusual financial behavior rather than actual money laundering.

Adopting a service-dominant logic, Lusch and Vargo (2014) and Manser Payne et al. (2021a) also highlight the central role of consumers in AI value cocreation processes. In particular, they suggest that consumers' characteristics, such as their previous banking experiences and trust or comfort levels when interacting with AI technologies such as robot advisors, may influence their AI usage intentions. Thus, consumers' perceptions of AI services, which might be different when offered by fintech companies rather than traditional financial organizations, should be taken into account when designing AI strategies. Manser Payne et al. (2021a) also investigate mobile banking AI service platforms, suggesting that service delivery and a customer's role in value cocreation change as AI is introduced into digital self-service technology channels. In addition, the authors suggest that consumers attribute more importance to the utilitarian and transaction-oriented value of mobile banking AI service platforms than to the hedonic, relationship-oriented value of such platforms. In this regard, researchers have also investigated the relationship aspect of AI technology in the context of financial services. In particular, Zhang et al. (2021) analyze consumers' preferences regarding robo-advisors, comparing them with human advisors in the context of financial services. On the one hand, the authors show that consumers rate human financial advisors with high expertise better than they rate robo-advisors in terms of performance expectancy and intentions to hire; on the other hand, there are no significant differences between robo-advisors and novice financial human advisors. Additionally, Moriuchi (2019) investigates virtual assistants in the context of transaction- and nontransaction-based online activities. This author highlights how advanced technologies, including voice assistants, have gradually been integrated into e-commerce shopping. By applying technology acceptance model constructs (perceived ease of use and perceived usefulness) and testing their effect on the engagement and loyalty between VAs and consumers, they suggest that consumers who use voice assistants to conduct transactional activities mainly use them for habitual purchases that do not require much reflection and analysis.

5. Discussions and Future Directions: A Research Agenda

Through our literature review, we uncover and describe the existing research trends regarding AI in the extant marketing research, ranging from methodological approaches involving AI techniques and applications to experimental and conceptual investigations of human-AI interactions, AI ethics, consumer behavior and psychology, company transformation and AI digitalization, social media management, e-commerce and financial services. Building upon these findings, we identify new questions that can drive this research toward a better understanding of the evolving field of AI in marketing.

5.1. Research Directions on AI Techniques and Applications

Due to the rapid development of AI techniques, we suggest research avenues for developing new marketing applications through machine learning (ML), deep learning (DL), neural networks (NNs), NLP and recommendation systems (RS) (Table 11).

As our TCCM review highlights, researchers are increasingly transforming their research approaches from more traditional methods to new AI-based methods, and they are starting to use behavioral data, which, thanks to big data and AI applications, are becoming increasingly available. However, in the new era of big data and powerful AI applications, researchers need to find the optimal balance between theory-driven and data-driven perspectives. For instance, domain theory-driven perspectives can guide searches for patterns via the identification of possible constructs and relationships that can be used in data-driven analyses (Maass et al. 2018). This can lead to collaboration across the two types of perspectives, thus contributing to data analytics and theory development.

Second, following Ma and Sun (2020), we suggest that marketers should introduce new techniques and demonstrate their value to marketing research (e.g., representation learning, reinforcement learning, deep generative models, and mixed methods). As access to big data, as well as big data harvesting, are drastically increasing (André et al. 2018; Calic and Ghasemaghaei 2020; Zhang et al. 2021), marketers need to improve the interpretability and predictions of their algorithms. In addition, new methods to analyze unstructured data, especially audio and video, and to examine hybrid data, potentially from multiple sources, should be developed, preferably using integrated models (Ma and Sun 2020). In addition, we suggest that NLP techniques should be developed to better foster consumer-AI interactions through chatbots, robots and social media.

Third, updated recommendation systems could be designed that adopt new approaches to detecting consumers' preferences and thus improve marketing mixes (Marchand and Marx 2020). For instance, new hybrid recommender systems (user-based collaborative filtering and content-based recommender systems; knowledge-based filtering; demographic-based systems; and utility-based systems) could be trained to capture consumers' preferences (Chinchanachokchai et al. 2021). However, consumer characteristics such as expertise and domain familiarity should also be taken into account (Chinchanachokchai et al. 2021). In this regard, Marchand et al. (2020) suggest that researchers could define new multiplicative models that account for nonlinear attribute preference functions and temporal changes in user preferences. We present a list of related research questions in Table 11.

Table 11 Cluster 1: research questions for AI techniques and applications

AI techniques and applications	Sub-group	Research questions
	ML, DL, NN	How researchers should balance data-driven and theory driven approaches? Which theoretical connections and implications have ML methods? Which new ML, DL, NN methods can be introduced for marketing research (PGM, representation learning, reinforcement learning)? Which methods could be developed to automate online decision-support capabilities of various marketing functions? Which new methods can be introduced to analyse unstructured data,

		especially audio and video, or data of format?
	NLP	Which NLP techniques can be developed to better foster consumers-AI interactions through AI-agent?
	RS	Which new RS could be designed to adopt new approaches for detecting consumers' preferences? How hybrid RS differently affect consumers' preference? How can RS help improve the marketing mix (e.g. defining capabilities, values, advantages, problems, and consequences for businesses in general and for marketing-related initiatives in particular)? How RS could optimize loyalty programs (e.g. analysing scanner or app activity data)? How consumer expertise affects product recommendation based on RS algorithms?

5.2. Research Directions on Human-AI Interactions in Service Settings

As shown by our TCCM review, many papers in this category still adopt traditional quantitative approaches and show a strong preference for declarative data. We suggest that researchers could benefit from new AI-based methods when conducting new research in this field. In this regard, by using behavioral data, academics might improve their understanding of consumers' interactions with AI-based agents in service settings. In addition, as many studies have been conducted in the United States and the UK, we suggest studying a wider of analysis to better comprehend the intercultural differences encountered when using and interacting with AI service agents.

We also suggest that research on human-AI interactions might benefit from investigating the way AI agent characteristics, consumer characteristics and contextual factors affect consumer-AI service interactions. Concerning AI agent characteristics, researchers might further investigate how anthropomorphism and human likeness affect consumers' interactions (Karimova and Goby 2021). For instance, researchers could focus on interface factors such as facial expressions and gestures to further explore the role of emotions in human-AI interactions (Chuah and Yu 2021; Yun et al. 2021) or on how the different vocal characteristics of AI-based assistants might affect user perceptions, thus conducting new research in the field of voice analytics (Hildebrand et al. 2020; Klaus and Zaichkowsky 2020; Whang and Im 2021). In addition to their vocal abilities, assistants' capacity to present visual information could be further investigated. In this regard, Whang and Im (2021) highlight how few new voice assistants are integrated with smart displays that present visual information (e.g., Amazon Echo Show). The authors call for new research to investigate the impact of such an expansion in the context of voice assistants.

Additionally, gender and identity disclosures of AI agents represent an insightful domain of research that is essential to designing ethical technologies free from biases and discrimination (Borau et al. 2021; Xueming Luo et al. 2019). In this regard, consumers' perceptions of gender-neutral bots or bots' identity self-disclosures could be further investigated (Xueming Luo et al. 2021).

In addition to agent characteristics, consumer characteristics (Davenport et al. 2020; Whang and Im 2021), such as a customer's age, gender, psychological traits and personality, and contextual factors, such as service failures (Belanche et al. 2020; McLean et al. 2021), hedonic versus utilitarian features (Granulo et al. 2021; Longoni and Cian 2020), high- versus low-involvement contexts (Whang and Im 2021), and collaborative versus competitive settings (de Bellis and Venkataramani Johar 2020; Sowa et al. 2021), could affect AI interactions, highlighting potential avenues for research. Longitudinal studies are also needed to comprehend the ways in which human-AI interactions evolve over time (Schweitzer et al. 2019; Whang and Im 2021). We present a list of related research questions in Table 12.

Table 12 Cluster 2: research questions for human-AI interactions in service settings

Cluster	Subtopic	Research questions
Human-AI interaction in service settings		
	AI agent characteristics	How alternative interface factors such as facial expressions and gestures affect consumers' interaction with AI assistants?

		How personality and social attributes of voice assistants affect consumers' AI interaction?
		How different vocal characteristics of voice-assistants affect users' perception?
		Would users perceive voice assistants with a screen (e.g., Echo Show, Siri) to be more persuasive than those with no screen (e.g., Echo Dot)?
		How a gender-neutral bot would be perceived compared to a male/ female bot?
		How presenting different identity framings of bots (disclosed versus undisclosed identity) affect consumers' intention to use the bot?
		Is there an ideal balance between the nature and extent of tasks and activities automated by AI or performed by human service agents?
	Consumer characteristics	How different consumers' groups (e.g., older age groups; vulnerable populations) may perceive and use voice assistants differently?
		How key consumer characteristics (personality, psychological traits) have an impact on the perception and attitudes towards AI agents?
		How do consumers-AI agent relationships (trust, intention to use) develop over time?
		How do consumers perceive emotional expressions of AI-agent?
	Context characteristics	How do consumers react to service failure delivered by AI-agent? Which are the consequences for the company?
		Does anthropomorphizing the AI-agent increase positive perception/ diminish negative perception in case of AI-based service failure?
		How giving consumers control over selecting the agent with whom interacting (human or bot) would affect the interaction and perceived service quality?
		How human-AI interactions differ in hedonic utilitarian contexts?
		How human-AI interactions differ in more or less risky contexts?
		Can consumers and AI agent collaboration (versus competition) improve the quality of the interaction and its outcomes?

5.3. Research Directions on AI Ethics

As many of the papers in this category are conceptual, we strongly highlight the need to conduct more empirical research on ethics in relation to AI technology while adopting both consumer and company perspectives. By extending the framework proposed by Du and Xie (2020), we propose that AI ethics can be investigated at different levels: the product level, consumer level, company level and societal level (Table 13). At the product level, manufacturers should define products and algorithms that are able to eliminate or at least reduce biases. In this regard, researchers should reflect on and comprehend how ethical values can be embedded in AI products (Du and Xie 2020; Murtarelli et al. 2021; Saura et al.2021). One way to effectively address ethical issues involving AI is to take into account the different characteristics of AI products, such as the relevant AI techniques and a product's level of interactivity and multifunctionality (Du and Xie 2020). By adopting a consumer perspective (Puntoni et al. 2021), researchers should also investigate consumers' main ethical concerns regarding AI products and suggest ways to overcome them. In this regard, consumers' perceptions of algorithm transparency (Ma and Sun 2020), privacy concerns (Thomaz et al. 2020) and cross-cultural variables such as individualism/collectivism (Shariff et al. 2017) might be investigated.

Further research avenues might also focus on the ways companies respond to the ethical challenges that AI introduces. In this regard, researchers might give new insights into companies' best practices when implementing AI applications (Du and Xie 2020; Lusch and Vargo 2014) in relation to privacy and data security (Gozman and Willcocks 2019; Thomaz et al. 2020) or job replacement and the augmentation-automatization balance (Du and Xie 2020; Meyer et al. 2020; Sampson 2021). At the societal level, many ethical issues arise, such as those related to accessibility and inequalities, power asymmetries, human well-being and the governance mechanisms (Du and Xie 2020; Murtarelli et al. 2021; Stahl et al. 2021).

Table 13 Cluster 3: research questions for AI ethics

Cluster	Subtopic	Research questions
AI Ethics		
	Product level	How different product characteristics raise different ethical concerns? Under what circumstances is a top-down or bottom-up approach to embed ethical values in AI-enabled products more effective? Under what circumstances is a hybrid method combining both approaches more effective? How can we reduce and eliminate AI biases and incorporate appropriate ethical values in AI-enabled products?
	Consumer level	Are consumers more or less likely to trust and purchase from companies/brands that are transparent about AI biases?

	To what extent are consumer perceptions of risks of AI-enabled products determined by product characteristics and consumer individual differences?
	How do consumers' AI product expertise and privacy risk awareness influence their evaluation and choice of AI-enabled products?
	To what extent do cross-cultural variables (e.g., individualistic vs. collectivistic, uncertainty avoidance) affect consumer reactions to privacy risks associated with AI-enabled products?
Company level	To what extent are inter-firm alliances, cross-sector partnership, or open innovation helpful to solve AI complex ethical issues?
	How should companies accurately gauge the extent of AI biases in their products and use the level of AI biases as a key parameter of product quality control?
	Which responsible data practice can companies implement to effectively preserve the privacy and security of consumer personal data?
	How companies should address augmentation-automatization?
	How should they integrate AI for augmenting their employees according to the task?
Societal level	What are the positive and negative effects of AI products on well-being?
	How to guarantee equal access to AI technology across different groups to avoid inequalities?
	How AI can increase power asymmetries and how this can be prevented?
	Are there any existing governance mechanisms as well as proposals for new ones, adequate in addressing AI ethical challenges? What are their impacts and possible side effects (e.g., a loss of social trust in existing mechanisms)?

5.4. Research Directions on Consumers' Behaviors and Psychology in the Era of AI

In this cluster, the TCCM review shows that traditional quantitative approaches such as experimental designs remain as preferred methodologies. Considering the progress of AI-based research methods, we suggest that researchers could begin adopting new approaches to collecting and analyzing their data. In addition, in this case, the United States is the preferred country for conducting research. However, as societies around the world are adopting AI technologies, researchers should also explore how the intercultural differences between different countries affect AI adoption. For instance, Brill et al. (2019) suggest that researchers should conduct cross-cultural analyses focused on AI products such as autonomous cars. At the theoretical level, although many researchers have started to investigate AI adoption intentions (de Bellis and Venkataramani Johar 2020; Huang and Qian 2021; Schmitt 2020; Shariff et al. 2017), there is still much uncertainty around these new technologies, and many questions still need to be answered (Table 14). In fact, as AI and technological innovations evolve, it is becoming increasingly important to understand how different types of AI (Huang and Rust 2018) and different levels of AI product automation (Huang and Qian 2021) affect trust and adoption intentions. In addition, it is important to comprehend the consumer characteristics and psychodemographic variables that might affect adoption. Researchers should also take into account the paradoxical nature of technology (Du and Xie 2020; Fournier 1998); for instance, they should investigate the effects of trade-offs between autonomy and efficiency (Dellaert et al. 2020) or between personalization gains and privacy issues (Brill et al. 2019; Cloarec 2020) on adoption intentions. Certain researchers also suggest that the usage of AI over time should be investigated through longitudinal studies, as this could eventually provide insight into the concept of *disadopting* AI technologies (Brill et al. 2019).

Also, the way consumers' decision-making is affected by AI technology through consumer choice and autonomy (André et al. 2018), seller influence, expertise, technology familiarity (Dellaert et al. 2020), product categories (Longoni and Cian 2020) and smart nudging (Mele et al. 2021) present interesting avenues of research. In this regard, algorithmic biases such as algorithm overdependence (Banker and Khetani 2019) or algorithm aversion (Dietvorst et al. 2015) are important topics of investigation. Moreover, we identify some research questions concerning consumers' engagement and satisfaction with AI technology. In this regard, researchers could investigate whether the increasing personalization of AI services actually augments customer engagement and satisfaction with brands and services (Brill et al. 2019; Perez-Vega et al. 2021). Brill et al. (2019) also suggest that we must truly comprehend whether autonomous technologies "kill brands" or whether they increase the importance of brands by maximizing consumers' satisfaction. To conclude, longitudinal studies should be conducted to comprehend how consumers' behaviors in relation to AI change over time.

Table 14 Cluster 4: research questions for consumer behaviors and psychology

Cluster	Subtopic	Research questions
Consumer behaviors and psychology in the era of AI	Adoption intention	How different automation levels (e.g., in self-driving cars) affect trust and intention to adopt the AI product?
		How consumers' characteristics (cultural backgrounds, psychographic variables) affect adoption intention of AI products?
		What are the distinct roles of locus of control, self-efficacy in the adoption process?
		How the trade-off between autonomy and efficiency affect adoption intention?
		How do users perceive the trade-off between personalization gains and privacy issues?
		How do consumers *disadopt* autonomous technologies (behavior cessation), for instance when they perceive those long-term determents outweigh short-term benefits?
		How intention to adopt or usage intentions evolve over time?
		How does the importance of perceived control change with the increasing adoption of autonomous technologies?
	Consumer decision making	Do AI recommendations reduce the scope of options that consumers consider?
		Does AI increase consumer susceptibility to seller influence?
		What dimensions of different AI product categories (e.g., utilitarian versus hedonic) strengthen or weaken consumer decision making?
		How domain expertise, involvement, time spent making decisions, or familiarity/repeated use of AI systems affect consumer decision making?
		Can consumers be persuaded to trust AI systems, even more than humans, in the eventuality that AI systems are sufficiently sophisticated to pass the Turing test?
		How smart nudging and choice architectures contribute to human actors' decision-making and value co-creation in positive and negative scenarios?
		How algorithm biases (such as overdependence or aversion) affect consumer decision making in different contexts?
	Consumer engagement	How do consumer engagement change and develop across different levels and types of AI?
		How customized responses from the firm enabled by artificial intelligence can impact on customer engagement?
	Consumer satisfaction	How brand satisfaction impacts expectations, trust and privacy concerns for digital assistants?
		Do autonomous technologies "kill brands" or do they increase the importance of brands?
		How consumer satisfaction and engagement with AI systems changeover time?

5.5. Research Directions on AI, Company Transformation and Strategy

The majority of the papers in this cluster are also conducted at a conceptual level. Thus, we strongly call for empirical research to shed light on the way companies are implementing AI technologies. Due to the rapid evolution of AI applications, companies need to learn to quickly adapt their strategies and business models to the new challenges that AI technology introduces. Flexibility and openness to innovation are becoming crucial to survival in this evolving landscape. In this context, there are many potential avenues for future research (Table 15).

First, it is important to understand how company decision-making can be augmented by AI and to identify the best practices that companies should adopt to implement AI-augmented decision-making (Makarius et al., 2020; Shrestha et al. 2021). For instance, best practices such as transparently reporting how algorithmically augmented decisions are made and educating organization members about the functioning of algorithmic engines, their respective costs and benefits and their effects on companies could be further investigated (Shrestha et al. 2021). In addition, new forms of business models that can be implemented to adapt to the new AI era could be investigated to better comprehend the new strategic frameworks in the business environment. Additionally, the AI-employee augmentation-automation balance, the way companies reskill and train their employees and the transformational learning that occurs in the context of AI systems are all interesting potential research avenues (De Bruyn et al. 2020; Makarius et al. 2020).

Finally, the way AI affects marketing across the different functions (analysis, segmentation, positioning, pricing decisions, communication and CRM) should also be further investigated (Huang and Rust 2021a, 2021b; Rust 2020). For instance, Davenport (2020) suggests investigating AI predictions regrading truly new products that that might involve more difficult forecasts and new ways of handling consumer disengagement due to automation.

Table 15 Cluster 5: research questions for AI, company transformation and strategy

Cluster	Subtopic	Research questions
AI, company transformation and strategy	Company decision making	How AI-algorithms affect decision-making processes within the organization? How do decision makers trust the output received from AI systems? Which best practices should decision makers adopt when using AI algorithms for decisions?
	Business model adaptation and digitalization	Which new business models have been developed to best implement and adapt to AI changes? How can organizational factors influence adaptation to AI systems? How will employee tasks change with AI systems? How can managers re-skill workers to work successfully with AI systems (e.g. through AI coaches)? What is the level of AI and employee interdependence? How does transformational learning occur with AI systems? How can humans more effectively transfer their tacit knowledge into AI machines?
	AI, marketing and service strategies	As AI advances in marketing, where does it provide the most value, and how is that changing over time? How can marketing organizations facilitate and systematize interactions between AI and marketing stakeholders? How well prediction AI–driven algorithms may extend to forecasting demand for really new products? How to balance data- and theory-driven market analysis? What happens when the customer is AI? How should marketers and AI collaborate to improve segmentation and positioning? How to manage customer disengagement due to automation?

5.6. Research Directions on AI and Social Media Management

Many of the research questions identified in relation to the cluster concerning social media management regard the way social media can be used to better comprehend consumer sentiments (Table 16). In this regard, as shown by the TCCM review, many studies have already applied AI to analyze consumers’ sentiments through their interactions on social media. However, researchers highlight the need to develop the literature and new methods to interpret unstructured data such as video, audio, and pictures to better comprehend consumer sentiments online and offer optimal personalized services and communication (Balducci and Marinova 2018; Davenport et al. 2020; Ordenes and Zhang 2019). In addition, researchers need to understand how to develop the best autonomous social media management systems, which can facilitate the provision of personalized, efficient services 24/7 (Capatina et al. 2020).

Table 16 Cluster 6: research questions for social media management

Cluster	Research questions
AI and social media management	
	How can firms interpret the content of images and videos that customers upload to social media websites to gauge trends in customer sentiment?
	How can deep learning techniques detect patterns in voice of videos to determine customer sentiment?
	How AI can analyze customer communication and other customer information (e.g., social media posts) in ways to devise future communications that are more persuasive or increase engagement?
	How might AI combine text and other communication inputs (e.g., voice data), actual customer behavior, and other information (e.g., behaviors of similar customers) to predict repurchases through social media platform?

5.7. Research Directions on AI, E-Commerce and Financial Services

Many research questions arise concerning the way online financial services and economic transactions will benefit from AI (Table 17). In this cluster, we call for more research to apply and develop AI-based methods to better comprehend AI in the financial sector and its use for economic transactions. In addition, we highlight the need to conduct research around the world to reveal the different intercultural approaches to AI in the financial sectors of different countries. On a theoretical level, following Manser Payne et al. (2021), we select some research questions that can drive future research toward a better comprehension of how bank activities are changing to meet consumer expectations. Research on AI also requires an improved understanding of the way financial institutions and fintech companies are implementing new technologies to drive AI investments and a better definition of the omnichannel environments able to guarantee a high level of service quality. We also call for research on consumer behavior in the context of financial services and e-commerce to facilitate a better understanding of consumer needs and how to satisfy them, for instance, by offering an optimal mix of online and offline interactions and implementing strategies that maximize consumer comfort, trust and satisfaction (Steinhoff et al. 2019).

Table 17 Cluster 7: research questions for e-commerce and financial services

Cluster	Research questions
AI, e-commerce and online financial services	
	What specific banking activities or tasks do consumers find more valuable in an AI context?
	To what degree does the financial institution's digital orientation drive AI investments?
	What AI strategies can the financial industry incorporate in an omnichannel environment to best service consumer needs?
	How does AI investments change consumer banking behaviors?
	What differences exist in consumer banking behavior between lower and higher levels of AI interactions?
	How do consumers' perceptions of AI services differ if offered directly by fintech companies vs traditional financial industry firms?
	What data privacy and security regulation is needed for consumers to trust AI banking and financial services?
	What is the optimal mix of online versus offline relational interactions?

6. Conclusion

Through a hybrid literature review, we describe the evolving marketing research in the field of AI. Despite the growing number of publications in this domain, there is still a high degree of uncertainty concerning the future applications of AI in the marketing and service sectors. For this reason, the first chapter of this work offers an overview of the current state of this literature, uncovering the different topics investigated by marketing researchers: AI methodological applications and techniques, AI-human interactions in service settings, the ethics of AI, consumer behaviors and psychology related to intelligent technologies, company transformation and strategies, social media management and financial services in the era of

AI. We conclude by proposing a research agenda, inviting present and future researchers to contribute to the evolution of this field.

7. Towards the Next Chapters: Chatbots and Autonomous Cars as AI Applications

The second part of thesis focuses on two different AI applications: chatbots (Chapter 2) and autonomous cars (Chapter 3). In this regard, we have shown in Chapter 1 that one of the main research streams identified in the literature focuses on the relationship between consumers and conversational agents, such as chatbots, in service settings. The growing interest of academics mirrors the increased diffusions of this technology, often implemented by companies to handle different type of services. The majority of the studies investigates consumers' interactions with AI agents in successful scenarios, often identifying the variables that increase usage and acceptance (Luo et al. 2019; Meyer-Waarden et al. 2020; Pizzi et al. 2020). However, very few studies have investigated how consumers are affected when interacting with these machines in the context of service failure (Belanche et al. 2020). We suggest that this type of investigation is important for three main reasons: 1) as the technology is still not mature enough to handle complex situations, chatbot often fails to successfully interact and communicate with consumers, thus improperly delivering the service; 2) the failing interaction with a machine could cause negative feelings and emotions which need to be addressed as they might have negative consequences for individuals, decreasing their well- being (Frow et al. 2019); 3) the failing interactions could also have negative consequences for the company, potentially decreasing their reputation and image (Belanche et al. 2020). Thus, the following chapter investigates consumers' negative attributions, emotional responses, and the way they cope with their negative emotions when interacting with AI-based service agents in failure scenarios.

Introduction

PART I
Defining AI in Marketing

Chapter 1. Artificial Intelligence in Marketing Research: Scientometric, TCCM Review and a Research Agenda

PART II
Practical AI Applications

Chapter 2. Rage Against the Machine: Investigating Consumers Negative Emotions, Attributions of Responsibility and Coping Strategies in AI-Based Service Failures

Chapter 3. Now, Take your Hands from the Steering Wheel! How Trust, Well-Being and Privacy Concerns Influence Intention to Use Semi- and Fully Autonomous Cars

PART III
On the Ethics of AI

Chapter 4. Consumers' Perspectives on AI Ethics and Trust: an Explorative Investigation of Ethical Concerns Towards Autonomous Cars and Chatbots

Overall Theoretical, Methodological, Managerial Contributions, Research Limits and Future Research Directions

PART II

PRACTICAL AI APPLICATIONS

CHAPTER 2

RAGE AGAINST THE MACHINE: INVESTIGATING CONSUMERS NEGATIVE EMOTIONS, ATTRIBUTIONS OF RESPONSIBILITY AND COPING STRATEGIES IN AI-BASED SERVICE FAILURE

1. Introduction

In today's digitalized world, technologies are taking the lead. Artificial intelligence (AI) in particular, defined as machines and systems able to perform tasks that normally require human intelligence, enriches a range of tools that can benefit marketing (Davenport et al. 2020; Huang and Rust 2021c). Thus, companies seek to enhance their customer services with intelligent systems, including service robots and chatbots (Ostrom et al., 2019). The infusion of rapidly improving technology into product and service settings means that humans are increasingly supported, augmented, and even substituted by machines (Ostrom et al. 2019), thereby changing the nature of service, customers' experiences, and customer–firm relationships (Huang and Rust 2018; Ostrom et al. 2019; van Doorn et al. 2017). For example, AI-based chatbots can provide customer service being able to mimic human communication using natural language processing and machine learning techniques, sensing their environment and operating without human involvement (Araujo 2018). The first chatbots mainly executed simple tasks, but current versions can provide more complex services, such as offering recommendations (Araujo 2018).

Reflecting these increasing capabilities, as of 2017, more than 100,000 chatbots were installed through Facebook Messenger (Araujo 2018). But even if consumers interact more often with them, they express some reluctance and skepticism about relying on chatbots. Some hesitance might be due to service failures created by these technologies, which still often fail to work properly, despite their development (Forrester 2019). Understanding how users perceive this form of technology-mediated communication, especially in difficult situations such as service failures and double deviations, is critical. In fact, the failing interaction with chatbots could cause negative consumers' feelings; potentially decreasing their satisfaction and well-being (Frow et al. 2019). Yet we still lack insights into customers' perception of AI-based service failure. In particular, we lack an understanding of how users attribute responsibility, their negative emotional responses and coping strategies in response to a service failure and double deviations involving AI-based technology such as chatbots (Belanche et al. 2019). In addition, the interactions between human users and AI-based agents likely feature varying degrees of anthropomorphic visual cues which may have unique effects on consumers' responses (Blut et al. 2021; Golossenko et al. 2020).

To advance such understanding, we structure our research around four key questions. First, how do customers' attributions of responsibility and negative emotional responses differ if the service is delivered by an AI-based chatbot, versus a human agent? Second, which coping strategies do users adopt to regulate their negative emotions when interacting with an AI-based chatbot versus a human agent? Third, are customers' coping strategies affected when adding anthropomorphic visual cues to the chatbot, through the potential influences of intentionality, which refers to the consumers' social perceptions that the chatbots has good or bad intentions and the ability to implement them (Kervyin et al. 2012)? Fourth, do anthropomorphic visual cues affect consumers' attributions of responsibility toward the chatbot and the company? In an effort to answer all of these research questions, we conduct three experimental studies in the airline context (Figure 8).

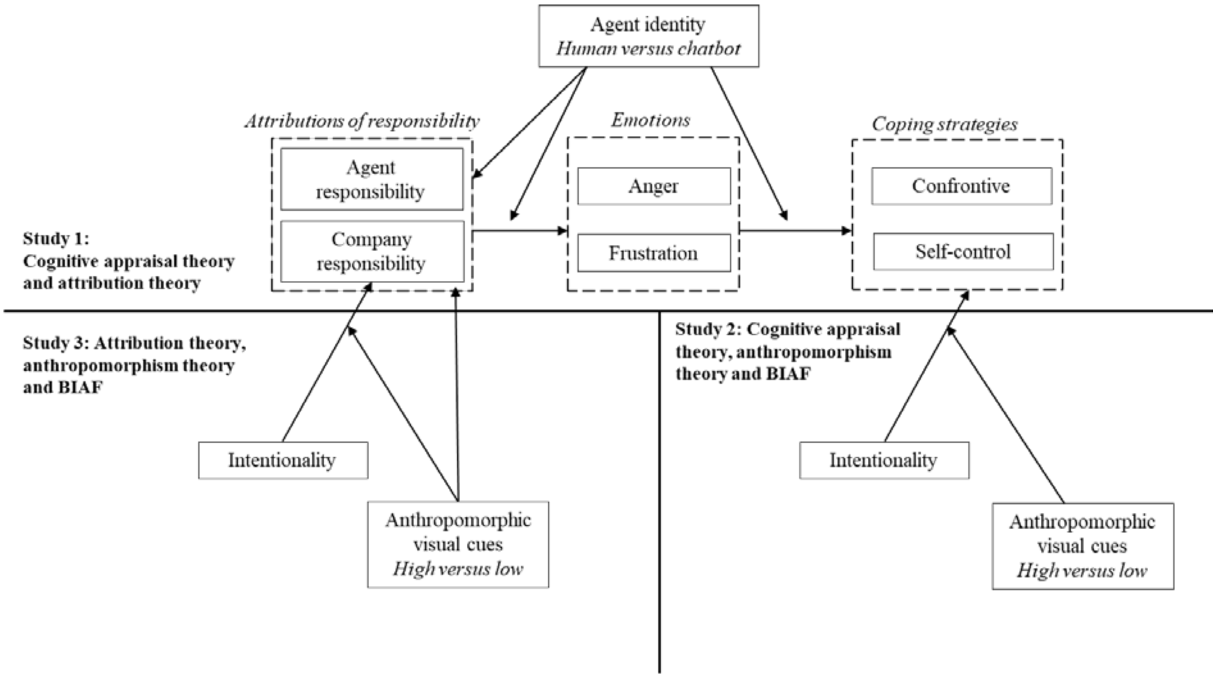
Specifically, in Study 1 (N = 122), we compare human–human and human–chatbot interactions, leveraging insights from Cognitive Appraisal Theory (Roseman 1991; Roseman et al. 1990) and Attribution Theory (Weiner 2000) to establish initial findings and a research framework. The results suggest that, when interacting with chatbots, consumers attribute higher responsibility for the failure to the company, compared to when they interact with a human agent, experiencing higher frustration. Despite being aware that they are interacting with a chatbot, respondents adopt confrontive coping strategies to express their anger and frustration to the machine, as they would in human interactions.

In Study 2 (N = 120), we extend the research framework to include anthropomorphic visual cues (high versus low) and the attributions of intentionality to the machine (Kervyn et al. 2012), identifying their effects on coping strategies. In particular, we seek to determine if manipulating chatbots visual cues diminishes consumers' negative responses and potentially offers an explanation for the adoption of emotion-focused and problem-focused coping strategies, such as self-control and confrontive coping. The results suggest that when customers attribute intentions and the ability to act on them to a chatbot, they are more willing to engage in confrontation with the machine, arguing their cases and looking for a solution. This effect is moderated by the anthropomorphic visual cues: the more the chatbot resembles a human, the more the perceived intentionality influences the confrontation.

Finally, in Study 3 (N=120) we focus on attributions of responsibility to the company, according to the anthropomorphic visual cues of the chatbot. Again, we confirm our research framework, as the results show that anthropomorphic visual cues may help to mitigate the negative attributions to the company. In fact, the more the chatbot exhibits human-like characteristics, the less the company is held responsible for the negative outcome.

To our best knowledge, this study represents one of the first researches investigating how consumers regulate their negative emotions when interacting with an AI-based agent in a service failure setting. Thus, we offer contributions to the emerging literature about service failure and consumer behavior theories in AI-based technology-based interactions.

Figure 8 General framework



2. Study 1: Human-Human Versus Human-Chatbot Interactions

2.1. Literature Review and Hypotheses Development

2.1.1. Chatbots in Service Encounters

Service robots are system-based, autonomous, adaptable interfaces that can be physical or virtual, as well as humanoid (i.e. anthropomorphic) or not, and can interact, communicate, and deliver services to users (Wirtz et al. 2018). As a specific type of service robot, chatbots are conversational agents that interact with users in a limited topic domain, by applying natural language processing to provide information, site guidance, or answers to frequent questions (Huang 2007). Lester et al. (2004) further define chatbots as technologies that exploit natural language, engaging users in text-based information-seeking and task-oriented dialogue for a broad range of applications. They achieve varying levels of artificial intelligence, and Huang and Rust (2018) suggest a classification based on four types of intelligence: mechanical (i.e., performing repetitive tasks automatically), analytical (i.e., processing information to solve problems and learn from it), intuitive (i.e., thinking creatively and adjusting to novel situations), and empathetic (i.e., recognizing and understanding other actors' emotions, affecting them, and responding appropriately). Advanced generations of AI (i.e., intuitive and empathetic) are still far from reality.

Human employees instead tend to exhibit deep understanding of their customers and deliver heterogeneous, individualized services based on their learning. Although they may have innate empathetic or intuitive intelligence, human service representatives require costly hiring, selection, training, and motivation efforts, which aim to make these human resources into a source of competitive advantage. Unlike humans who express their unique capabilities, perceptions, and emotions (Wirtz et al. 2018), which creates service heterogeneity; chatbots acquire knowledge throughout the system quickly, and then leverage their AI to find consistently optimal solutions, offering more homogeneous services (Huang and Rust 2018). Most existing chatbots achieve only mechanical or analytic intelligence though, so even if they offer cost and time efficiencies, they also may fail to satisfy consumers and cannot differentiate the service to produce a competitive advantage. Efficient, consistent, pre-programmed scripts even might create a risk of failure, if they do not represent appropriate responses to users' requests.

2.1.2. Service Failures and Double deviations

A service failure occurs when perceived service performance falls below the customer's expectations (Hess et al. 2003). It poses serious risks to the company, because it might lead to customer dissatisfaction (Bitner et al. 2000), switching (McCollough et al. 2000), avoidance, or vengeance (Grégoire and Fisher 2008). After a service failure, customers also expect effective recoveries (Bitner et al. 1990), defined as activities by which a company seeks to resolve the problem. However, double deviation can arise when, after a service failure, the company fails to resolve the situation creating a secondary failure with intense negative consequences, including customer anger and frustration (Gelbrich, 2010; Gronroos, 1988). (Bitner et al. (2000) suggest that service failures may have unique characteristics if the encounters involve technology. For example, when studying self-service technologies, Meuter et al. (2018) find that customers recognize when the technology causes the negative service outcome and respond with negative emotions due to their perceptions of inconvenience, uncertainty and performance ambiguity.

2.1.3. Cognitive Appraisal Theory of Emotions and Attribution Theory

Following a service failure and a double deviation which are incongruent with their expectations, consumers experience negative emotions, which ultimately reflect the combinations of their appraisals (Gelbrich 2010; Roseman 1991). Appraisal theories further clarify that emotional responses are not determined by events per se but by people's evaluations and interpretations of those events (Lazarus 1991; Roseman 1991). Basic appraisal dimensions include goal relevance, which refers to whether the event enables the person to attain desired goals (Lazarus 1991). A further dimension refers to causal attribution, which describes whether an outcome is perceived as caused by impersonal circumstance or another person (Bagozzi et al. 1999; Roseman 1991). External attributions imply that the individual blames someone else for an (aversive) situation (Gelbrich 2010). Depending on the appraisal of causal attribution, which may be conscious or unconscious, individuals thus experience emotions (Bagozzi 1999; Roseman 1991). Also Attribution Theory (Folkes 1984; Weiner 2000) suggests that attribution of responsibility influence affective reactions. Attribution Theory has been widely applied to investigate consumer responses to failure (Choi and Mattila 2008), including in human–technology interactions with service robots (Jörling et al. 2019). Such studies suggest that when interacting with service robots, humans tend to blame machines less for negative outcomes (Jörling et al. 2019). In addition, individuals make stronger attributions of responsibility for negative service outcomes to humans than to AI-based service robots (Belanche et al. 2020). This is because robots have less control over the task they perform than human service providers (Leo and Huh 2020). In addition, consumers tend to attribute higher responsibility for the negative outcome to the firm than to the frontline service robot (Belanche et al. 2020). Indeed, if less blame is assigned to the robot, customers might tend to look for another culprit. Thus, in the case of AI-based service failure, the company might be perceived as more culpable because it implemented the technology that delivered the poor service (Leo and Huh 2020).

Prior research on chatbots and robots also indicates that people perceive computational systems as having less emotional capability, intentionality, and agency, including abilities to exhibit self-control, morality, memory, emotion recognition, planning, or thinking, relative to other humans (Gray et al. 2012). If robots appear to lack intentionality - defined as the tendency to have good or bad intentions and the ability to implement them (Kervyin et al. 2012) - they cannot purposefully cause a service failure. Thus, they cannot be blamed for the negative outcome.

To test external attributions of responsibility to an agent (human or chatbot) or to the company, we investigate a service failure scenario in which the customer is not responsible. In these situations, consumers tend to look for an external actor to blame (Weiner 2000). We predict that in an AI-based service failure, consumers more frequently target the firm rather than the chatbot which cannot be directly accountable due to its lack of intentionality (Gray and Wegner 2012). If instead the service failure involves a human employee, customers might attribute the blame to the human agent, considered as directly responsible for the failure (Weiner 2000). Formally, we propose that:

H1: Customers attribute more responsibility for the failure to human agents than to chatbots.

H2: Customers attribute more responsibility for the failure to the company if the agent is a chatbot rather than a human agent.

2.1.4. Attributions of Responsibility and Emotions

Emotions are defined as mental states of readiness that are evoked by the evaluation of events on different dimensions of appraisal (Bagozzi 1999). Following a service failure, which is incongruent with customers' expectations, individuals experience negative emotions (Gelbrich 2010; Roseman 1991). Anger against a service provider and frustration about the negative situation are common emotional reactions to service failures (Gelbrich 2010; Kalamas et al. 2008). In this regard, research shows that when people consider another person as responsible for a negative outcome, they tend to experience anger against the person they blame (Bonifield and Cole 2007; Roseman 1991). In particular, if customers blame service providers for a failure, they experience anger against him or her (Bonifield and Cole 2007). However, the relationship between attributions of responsibility and negative emotions may change, depending on the identity of the agent (Belanche et al. 2020; Leo and Huh 2020). Indeed, research shows that individuals tend to perceive a service failure provided by a human and by a robot differently (Belanche et al. 2020; Leo and Huh 2020). If on the one hand there is evidence that users may experience strong negative emotions towards chatbots, exhibiting verbal disinhibition, rudeness, and violating conversational norms; on the other hand, the chatbot cannot be directly considered as responsible for the failure, because it lacks the necessary cognitive abilities to develop purposeful intentions (Grey et al. 2017; Leo and Huh 2020). Thus, if the attributions of responsibility towards the chatbot are weaker, anger toward the AI-based service provider should also be weaker, compared to the human service agent. In other words, the effects of external attributions of responsibility on anger may be stronger when the agent is a human (Weiner 2000) rather than a chatbot. Thus we propose:

H3: Attributions of responsibility to the agent (a) have a positive effect on anger, (b) moderated by the agent's identity, such that the positive effect is stronger for human versus chatbot agents.

Research shows that when the negative outcome is not directly due to the service agent but rather reflects the circumstances and situational factors beyond the agent control, such as the actions implemented by the company, customers might experience frustration about the uncontrollable situation instead of anger towards the agent (Roseman 1991). As stated before, when interacting with a chatbot, consumers do not perceive it as directly responsible (Gray and Wegner 2012; Lee 2018). So, in the case of AI-based service failure, individuals may rather experience higher frustration about the situation rather than anger toward the AI-based service agent, as the events are perceived as beyond the chatbot's control and intentions (Leo and Huh 2020). However, as the decision of implementing a chatbot may be attributable to the company, which has decided to implement the chatbot, consumers may indirectly consider the firm as responsible for the negative outcome, feeling frustrated about a situation they and the AI-based service agent cannot control. On the other hand, when interacting with the human agent, the attribution of responsibility towards the company might be lower, as it might be shared with, or entirely attributable to the human employee, rather experiencing anger against the agent than frustration about the situation (Belanche et al., 2020). Thus, we predict a moderating effect of the agent's identity on the relationship between attributions of responsibility to the company and frustration.

H4: Attributions of responsibility to the company (a) have a positive effect on frustration, (b) moderated by the agent's identity, such that the positive effect is stronger for chatbot versus human agents.

2.1.5. Emotions and Coping Strategies

When they experience negative emotions, people adopt coping strategies both to deal with the aversive situation and to regulate their feelings and emotions (Gelbrich 2010; Lazarus 1991; Roseman 1991). Coping strategies can generally be classified as problem-focused or emotion-focused (Folkman and Lazarus 1984). The former aims to deal with specific aspects of the problem by changing the environment and looking for solutions to overcome an obstacle; the latter instead works to regulate personal emotions and reduce distress, without altering the situation or solving the problem (Folkman and Lazarus 1984). In service failures, one common strategy that consumers may use to regulate their negative emotions is confrontive coping, a problem-focused strategy that refers to aggressive efforts to change the situation. Confrontive coping usually involves "showing displeasure toward the person perceived to be the source of the problem" (Yi and Baumgartner 2004, p. 306). When adopting confrontive coping, it is common for consumers to display aggressive interpersonal interactions that help regulate negative emotions (Bonifield and Cole 2007; Folkman and Lazarus 1984). Consumers might also persuade and pressure the service agent to fix the problem and insistently complain about the situation (Yi and Baumgartner 2004). Confrontive coping is the primary form of coping associated with consumers' anger (Yi and Baumgartner 2004). In fact, if a service failure is attributed to a human employee, who appears responsible for it, consumers often feel angry against the service provider and adopt confrontive coping strategies to vent these emotions and to actively ask for solutions (Bonifield and Cole 2007; Gelbrich 2010; Kalamas et al. 2008). However, as chatbots are still at a mechanical and analytical level of intelligence, they still fail to understand consumers' emotions (Davenport et al. 2020; Huang and Rust 2018). In addition, even if they can simulate emotions and empathy, customers understand that these emotional representations are superficial, and they respond accordingly (Gabbott et al. 2011). In particular, they might be less keen in confronting, venting, and expressing their negative emotions to a service chatbot that is unable to comprehend their feelings, as they would do with a human provider (Gelbrich et al., 2021). Thus:

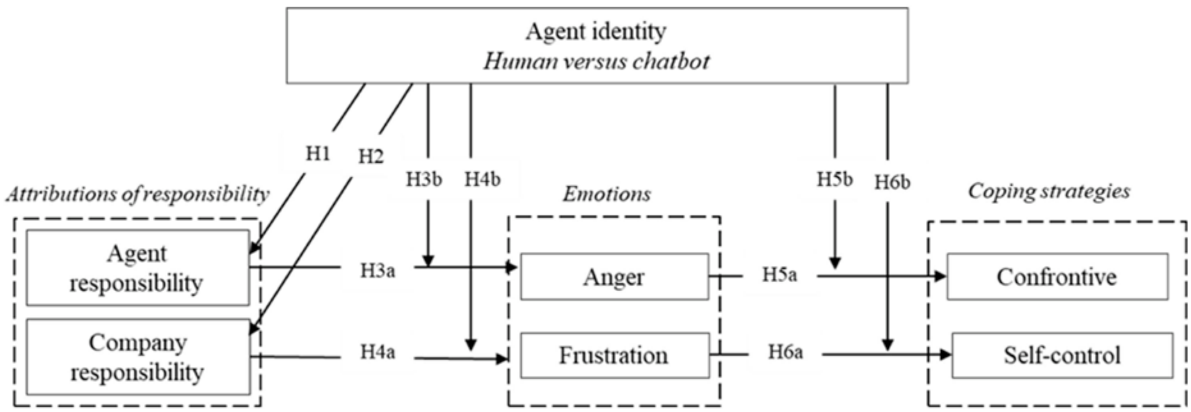
H5: Anger (a) has a positive effect on confrontive coping, (b) moderated by the agent's identity, such that the positive effect is stronger for human versus chatbot agents.

Other negative emotions do not feature direct external attributions, such as frustration (Gelbrich 2010). According to the literature, feelings of frustration about an uncontrollable situation foster emotion-focused strategies, such as self-control (Folkman and Lazarus 1984 ; Yi and Baumgartner 2004). In this case customers try to keep the feeling to themselves, using a self-control strategy to limit their expression of emotions, particularly negative ones. Consumers tend to seek self-control if the source of the failure is due to events beyond their control (Folkman et al. 1986; Yi and Baumgartner 2004). Psychological literature even operationalizes self-control as persistence in the face of frustration (Muraven and Slessareva 2003; Roseman 1991) Consistently, we propose that because chatbots are not perceived as directly responsible for the failure, consumers feel more frustrated about the situation and cope with their negative feelings by controlling their emotions.

H6: Frustration (a) has a positive effect on self-control, (b) moderated by the agent's identity, such that the positive effect is stronger for a chatbot versus a human agent.

Figure 9 shows the hypotheses formalized in the conceptual model.

Figure 9 Conceptual model of Study 1



2.2. Methodology

2.2.1. Experimental Design

The air travel industry is a relevant study context as it offers frequent opportunities for interactions and creates frequent service failures (Vázquez-Casielles et al. 2007). We use a between-subject experimental design and manipulate agent identity (human vs. chatbot), then assign participants randomly to the human or chatbot service agent. Firstly, participants read a description of the service failure (Appendix 1). According to the description, a consumer was on a business trip and his/her luggage went missing. A few days later, he/she still had not received any information about his/her missing luggage. Therefore, he/she contacted the airline's recovery chat agent to request more information and he/she was confronted with either a human service agent or an AI-based chatbot. Thus, we manipulate the identity cue informing participants whether the online chat agent was managed by a human or a chatbot (Go and Sundar 2019).

Next, the participants view a short video, depicting an interaction with the service agent: a human service agent in group 1 (Figure 10), and a chatbot in group 2 (Figure 11). In the video showing the interaction with the human, the service agent introduces himself as "Jack, the customer service agent representative of the airline"; in the video showing the interaction with the chatbot, the agent introduces itself as "Jack, the airline chatbot". The video script we wrote for this study is based on an in-depth analysis of real-life interactions with service providers and chatbots implemented by different airlines (Appendix 2). In both settings, service agents fail to help the consumer locate the luggage.

Figure 10 Sample stimulus of the video depicting interaction with the human service agent

Figure 11 Sample stimulus of the video depicting interaction with the chatbot

2.2.2. Sample

In total, a convenience sample of 122 respondents participates in this online experiment, 66.40% are women and 33.60% are men. Age and gender distributions of the sample are presented in Table 18. The experiment is conducted online in November 2019. Participants are randomly assigned to one of the two conditions (human agent; chatbot). Each group has 61 participants.

Table 18 Sample description of Study 1

	Gender	Total

		Women	Men	
Age	18-29	65	22	87
	30-39	9	11	20
	40-49	4	3	7
	50-59	2	4	6
	60-69	0	1	1
	>70	1	0	1
Total		**81**	**41**	**122**

2.2.3. Measurement Scales

All the measures use seven-point Likert-type scales, ranging from 1 "strongly disagree" to 7 "strongly agree." To operationalize the different concepts, we turn to existing measurement scales, including anger, frustration, and blame attribution measures from Gelbrich (2010) and Roseman (1991); confrontive coping strategy from Yi and Baumgartner (2004) and self-control from Yi and Baugmenter (2004). To check the ecological validity of our studies, we measure the realism of the scenario with three items from Bagozzi et al. (2016): "The scenario is realistic", "The scenario is believable" and "It was easy for me to put myself in the situation of the customer." The three items indicate our experiment offers an ecologically valid setting (M = 6.01, SD = .93). With a confirmatory factor analysis (Hair et al. 2013), we identify and keep items with factor loadings greater than .7. We drop items with lower loadings. The loadings are significant at the .001 level. The Cronbach's alpha exceeds .7, indicating good reliability, and the AVE values are higher than .5 (Table 19). We check for discriminant validity by calculating the square roots of AVEs of the constructs and comparing them with the correlations between constructs (Hair et al. 2013). All factor loadings exceed the cross-loadings, and the square roots of AVEs are greater than cross-correlations (Table 20). Thus, the data satisfy conventional requirements for reliability, convergent validity and discriminant validity. The model fit is acceptable with Chi²/DF < 5 (Byrne 2006), CFI >.80 (Bentler 1990), TLI > .80 (Bentler and Bonett 1980) and RMSEA = .08 is close to the standard suggested by Browne and Cudeck (1992) (Table 21).

Table 19 Reliability and convergent validity of the scales

	SE	*p*
Anger (Gelbrich 2010; Roseman 1991) α=.906; AVE=.764		
I feel angry with the customer service employee/chatbot	.851	< .001
I feel mad at the customer service employee/chatbot	.888	< .001
I feel furious with the customer service employee.	.883	< .001
Frustration (Gelbrich 2010; Roseman 1991) α=.791; AVE=.621		
I feel frustrated about the situation[a]	.587	< .001
I feel disturbed by the situation.	.862	< .001
I feel annoyed at the situation.	.746	< .001
Confrontive (Yi and Baumgartner 2004) (α=857, AVE=.525)		
I would have let the customer service employee/chatbot know how angry/frustrated I was.	.728	<.001
I would have argued my case.	.714	< .001
I would have continued to interact with the customer service employee/chatbot to complain about the situation.	.755	< .001
I would have talked more with the customer service employee/chatbot about the problem to ask to correct it. [a]	.533	< .001
I would have expressed my feelings without reservation	.708	<.001
I would have tried to get the customer service employee/chatbot to change his/her mind.[a]	.565	<.001
Self-control (Yi and Baumgartner 2004; Folkman et al. 1986) α=.839 ; AVE=.730		
I would have tried to keep my negative feelings to myself.[a]	.491	< .001
I would have kept others from knowing how bad the service is.[a]	.401	<.001
I would have tried not to act too hastily or follow my first hunch	.824	< .001
I would have tried to keep my negative feelings from interfering.	.875	< .001
Agent/chatbot responsibility (Gelbrich 2010; Roseman 1991) α=.819; AVE=.699;		
The reason for th service feailure is something the customer service employee/chatbot had control over.	.847	< .001
To prevent the service failure there are actions the customer service employee/chatbot could have taken but has not.	.821	< .001

The customer service employee was responsible for the failure. [a]	.661	<.001
Firm responsibility (Gelbrich 2010) α=.738; AVE=.700		
The airline is responsible for this service failure.	.761	< .001
The problem encountered is all the fault of the airline.	.831	< .001

[a]=items dropped

Table 20 Discriminant validity, Study 1

Construct scale	Descriptives		Correlations					
	M	SD	1	2	3	4	5	6
1. Agent responsibility	3.995	1.520	**.834**					
2. Company responsibility	5.815	1.166	-.119	**.797**				
3. Anger	5.448	1.397	.342**	.124	**.874**			
4. Frustration	6.196	1.365	-.002	.229*	.267**	**.806**		
5. Confrontive	4.946	1.365	.411**	-.059	.480**	.198*	**.726**	
6. Self-control	3.750	1.377	-.018	-.127	-.216*	-.060	-.291**	**.850**

Scales range from 1 (strongly disagree) to 7 (strongly agree). The AVEs' (average variance extracted) square roots are presented in bold characters
* p<.05, ** p<.01

Table 21 Measurement Model Fit Index

χ^2	df	RMSEA	CFI	TLI
394	215	.08	.84	.82

2.3. Results

2.3.1. Attributions of Responsibility

With a t-test, we compare attributions of responsibility in human–human versus human–chatbot interactions (Table 22). Attributions of responsibility are significantly higher (t = -2.082, p < .05) in the human–human (M = 4.278, SD = 1.504) than the human–chatbot interaction (M = 3.713, SD = 1.495), in support of H1. Attributions of responsibility to the company are greater (t = 3.714, p < .001) in the human–chatbot interaction (M = 6.188, SD = .979) than the human–human interaction (M = 5.442, SD = 1.225), so we find support for H2.

Table 22 Attributions of responsibility, Study 1

	t	*p*	Human		Chatbot		Hypothesis
			Mean	**SD**	**Mean**	**SD**	
Agent responsibility	-2.082	<.05	4.278	1.504	3.713	1.495	H1: supported
Company responsibility	3.714	<.001	5.442	1.225	6.188	.979	H2: supported

2.3.2. Attributions of Responsibility and Emotions

The results of the moderation analysis conducted with the Process macro for SPSS model 1 (Hayes 2018), show that attributions of responsibility to the agent do not have significant effects on anger (b = -.192, SE = .249, t = -.774, $p > .05$), in contrast with our prediction in H3a. Yet we find a significant moderation effect of agent identity in the relationship between attributions of responsibility and anger (b = .351, SE = .157, t = 2.237, $p < .05$). This result supports our prediction in H3b, indicating that if the customers blame the service failure on human agents, it has a significant stronger positive effect on anger (b = .510, SE = .110, t = 4.608, $p < .001$) than when they blame a chatbot (b = .159, SE = .115, t = 1.426, $p > .05$). We also note that attributions of responsibility to the company have a significant positive effect on frustration, as predicted in H4a (b = .526, SE = .265, t = 1.979, $p < .05$). Agent identity does not significantly moderate the relationship (b = -.204, SE = .157, t = -1.294, $p > .05$), so we must reject H4b (Table 23).

Table 23Attributions of responsibility, emotions, and agent identity, Study 1

	b	*SE*	*t*	*p*	R^2	Hypothesis
Agent responsibility → Anger	-.192	.249	-.774	>.05	.167	H3a: not supported
Agent responsibility * Agent identity → anger	.351	.157	2.240	<.05		H3b: supported

Company responsibility → frustration	.526	.265	1.979	<.05	.066	H4a: supported
Company responsibility * Agent identity → frustration	-.204	.157	-1.294	>.05		H4b: not supported

2.3.3. Coping Strategies

As we predicted in H5a, anger has a significant positive effect on confrontive coping (b = .642, SE = .248, t = 2.584, *p* < .01), but because agent identity does not significantly moderate this relationship (b = .107, SE = .154, t = -.696, *p* > .05), we cannot confirm H5b (Table 24). That is, anger's positive effect on confrontive coping arises whether customers interact with a human agent (b = .436, SE = .106, t = 3.999, *p* < .001) or a chatbot (b = .534, SE = .112, t = 4.763, *p* < .001). Concerning frustration, it does not significantly affect self-control (b = -.158, SE = .418, t = -.378, *p* > .05) regardless of the agent's identity (b = .054, SE = .261, t = .209, *p* > .05). Thus H6a and H6b are not supported.

Table 24 Emotions, coping strategies, and agent identity, Study 1

	b	**SE**	**t**	***p***	R^2	Hypothesis
Anger → confrontive	.642	.248	2.584	<.01	.263	H5a:supported
Anger * Agent identity → confrontive	-.107	.154	-.696	>.05		H5b: not supported
Frustration → self-control	-.158	.418	-.378	>.05	.032	H6a:not supported
Frustration * Agent identity → self-control	.054	.261	.209	>.05		H6b: not supported

2.4. Discussion

When interacting with an AI-based chatbot in the context of service failure after a double deviation, customers blame more the company rather than the chatbot for the negative outcome. This result is in line with recent research showing that customers attribute responsibilities to the firm rather than the frontline robot (Belanche et al. 2020). One possible reason is that customers expect employees to improve after a poor service encounter, but expect little improvement in performance from robots (Belanche et al. 2020). We also suggest that individuals tend to blame less the chatbot due to the lack of perceived intentionality of the machine (Gray and Wegner 2012; Lee 2018). In this respect, since the chatbot has no sense of purpose and no control over its actions, it cannot be considered as responsible (Leo and Huh 2020). On the one hand, when customers interact with AI-based chatbot, they attribute responsibility to the company experiencing frustration about the negative situation that they cannot control (Gelbrich 2010; Roseman 1991). On the other hand, when interacting with human agents, the attribution of responsibility includes the employees and the company, increasing customers' anger toward the human agent blamed for the poor service (Bonifield and Cole 2007; Gelbrich 2010). Consistently, research suggests that people react with anger when they attribute responsibility for a negative event to another person and perceive that the other person could have prevented the event from occurring (Su et al. 2018). In this case, anger is characterized by a willingness to attack the perpetrator of the negative event in order to punish the person or seek redress (Beaudry and Pinsonneault 2010; Su et al. 2018). In contrast, when consumers attribute the event to external factors, they may feel frustrated about the situation (Gelbrich 2010). In the case of AI-based service providers, the company's decision to implement such a machine can be considered the cause of failure, as the chatbot is not directly responsible for the outcome. Thus, even if participants experience negative emotions in both conditions, their emotional responses differ when interacting with a human and a chatbot, according to their attributions of responsibility. In contrast, our results show that their coping strategies are similar; anger fosters confrontive coping strategies in both human–human and human–chatbot service failures. Thus, we observe that despite being aware of interacting with a chatbot, respondents express their negative emotions to the machine as they do when interacting with a human agent. This finding is consistent with previous research showing that individuals tend to apply social norms to interactions with machine, which may even include feelings of confrontation with the machine (Angeli and Brahnam 2008; Nass and Moon 2000).

3. Study 2: Human-Chatbot Interactions, Anthropomorphic Visual Cues and Coping Strategies

The first study suggests that despite being aware of interacting with a chatbot that cannot truly understand their emotions, individuals tend to use similar coping strategies to regulate their negative emotions as they do in human-human interactions. In particular, they tend to engage in confrontation and take their emotions out on the chatbot, just as they do with humans. Despite a growing stream of research and anecdotal evidence support these findings (Angeli and Brahnam 2008; Beaudry and Pinsonneault 2010), there is still a lack of understanding on why individuals apply such social behaviors to interactions with bots. In this regard, research suggests that cues of humanness might predispose users to evaluate the interaction according to their prior experiences with humans (Go and Sundar 2019). Simply evoking external characteristics linked to a human (e.g., pair of eyes) can have strong effects, including prompting assumptions of a moral code or invocation of social norms (Wiese et al. 2017). The physical human-like features of a chatbot may foster perceptions of anthropomorphism, creating a sense of human connection with non-human actors (Blut et al. 2021; van Doorn et al. 2017). Moreover, research suggests that people not only attribute superficial human characteristics to machines (e.g., a human-like face or body), but also tend to assume certain intentions behind observed actions (Epley 2018). Thus, when two individuals interact, they tend to make inferences about each other's thoughts and intentions from observing each other's behavior (Gray et al. 2012). When interacting with chatbots, individuals may also unconsciously make inferences about what the machine is thinking, feeling, and intending to do, adapting their behaviors accordingly (Wiese et al. 2017). For these reasons, we draw from Kervyin et al. (2012) integrating the construct of intentionality, which refers the intentions and the ability to enact those intentions of a specific non-human entity.

We build on our research framework used in Study 1, investigating anthropomorphic visual cues and perceived intentionality of the chatbot, and their effect on coping strategies. Thus, we focus on our third research question related to whether attributing human-like characteristics and imputing intentions and the ability to implement them to the chatbot explains the activation of confrontive coping strategies and self-control.

3.1. Literature Review and Hypotheses Development

3.1.1. Anthropomorphic Visual Cues

Designers have been increasingly implementing anthropomorphic visual cues in chatbots and service robots to enhance their degree of humanness (Blut et al. 2021; Go and Sundar 2019). Research shows that one way to humanize non-human objects is to assign them a name, a gender, or human-like physical characteristics (e.g., a face). In this regard, to make chatbots look like humans, human figures and pictures are often used (Go and Sundar 2019). The more human characteristics the non-human object has, the more it is represented in a way that activates a "human" schema, creating some degree of perceived similarity to humans. Beyond that, the usage of facial expressions, interaction and communication through speech and conversations play a key role in enhancing human-likeness (Blut et al. 2021). Embedding a technology or a product with anthropomorphic visual cues can increase the perceptions of anthropomorphism (Aggarwal and McGill 2007; Kim and McGill 2011). Anthropomorphism refers to people's tendency to attribute humanlike characteristics, intentions, mental and emotional states, and behaviors to nonhuman objects (Aggarwal and McGill 2007; Epley et al.

2018; Golossenko et al. 2020). Blut et al. (2021) consider anthropomorphism as a basic psychological process that can facilitate social human–nonhuman interactions. Anthropomorphism can be induced by making the object features resemble a human face (Kim et al. 2016), or a body (Kim and McGill 2011), or by presenting it as an avatar. When people anthropomorphize brand characters, mascots, avatars and entire brands (Kim et al. 2016) they create relationships with them (Golossenko et al. 2020; Kim et al. 2019; MacInnis and Folkes 2017). Individuals also exhibit such tendencies toward physical robots, chatbots, and other AI (Blut et al. 2021). Also verbal content seems critical for creating believable, lifelike, virtual characters that appear capable of intentions (Lee 2010). According to MacInnis and Folkes (2017) verbal marketing tactics also appear to activate human schemas and lead consumers to perceive nonhuman objects in human-like terms. For example, first-person language can promote perceptions of human-likeness (Golossenko et al. 2020; Waytz et al. 2014).

3.1.2. Intentionality

When interacting with each other, humans seek to determine whether the other is a "friend or foe", acting on his/her either friendly or hostile intentions (Fiske et al. 2007). The capacities to be positively or negatively intentioned toward other individuals and to act accordingly are universal dimensions of social cognition (Čaić et al. 2018; Fiske et al. 2007). In this regard, Fiske et al. (2007) propose the e Stereotype Content Model, according to which the two dimensions of competence and warmth organize the way people perceive the social world around them. Warmth includes perceptions of helpfulness, sincerity, friendliness, and trustworthiness, activated when the individual perceives the other party as well-intentioned. Competence includes perceptions of efficiency, intelligence, conscientiousness, and skill (Fiske et al. 2007). Drawing from Fiske et al. (2007) Kervyin et al. (2012) propose an updated and more parsimonious model: the “Brands as Intentional Agents Framework” (BIAF). According to the BIAF, people enter into relationships with brands as intentional agents such that they attribute mental states (e.g., positive or negative intentions) to these non-social objects. Then, customers' brand perceptions vary, according to how well or badly intentioned they perceive the brand to be (intentions) and how capable it is of implementing its intentions (ability). According to Fiske et al. (2012, p. 206) “intent is the underlying concept behind warmth, and the novelest idea in viewing non-human entities as people”. The concept of intentionality is used to emphasize the perceptions that an entity has intentions and the ability to enact those intentions. In addition, psychological research has emphasized the need to investigate the perceptions of technologies as intentional agents (Wiese et al. 2017). In fact, intentionality can positively affect human–robot interaction by fostering feelings of social connection, activating areas in the human brain involved in social-cognitive processing (Wiese et al. 2017). According to MacInnis and Folkes (2017) calling some objects "intelligent agents" (e.g., Siri) may increase such perceptions of intentionality and attributions of mental states. Also, attributing human-like features to non-human objects can elicit consumers' perceptions that the object can form intentions, make moral judgments thus acting positively or negative and having self-serving motives (MacInnis and Folkes 2017; Waytz et al. 2010). Attributions of mental states and intentions have also been studied in the context of robots, intelligent technologies and other AI (van Doorn et al. 2017; Wiese et al. 2017). From a social cognition perspective, human actors may perceive human-like robots in terms of the two dimensions of intentions and abilities that might emerge during social interactions (Čaić et al. 2019; Fiske et al. 2007; Kervyin et al. 2012). In fact, advanced technologies which are able to mimic human appearances and behaviors allow such non-human agents to exhibit affect and intentionality (Čaić et al. 2019). Thus, in the present study, the concept of intentionality refers to the social perception that the non-human entity is perceived as endowed with social cognition, in particular with positive, purposeful intentions and the ability to implement them. In this regard, the construct differs from the attributions of intentionality formalized by attribution theorists. In fact, intentionality in Attribution Theory refers to whether the actor intended the result to occur, considering the cause of the service failure to be the outcome of the provider's intention, that is, the provider not wanting to meet all consumers' expectations (Varela-Neira et al. 2014). However, in this study we focus on consumers' social perceptions that the AI-based agent is endowed with intentions and ability to implement them independently on the service outcome. Investigating this concept is even more critical, as, depending on its characteristics, consumers might not perceive the AI-based service agent as endowed with mental states and intentions, thus affecting the way they develop the relationship and the transaction. In this regard, van Doorn et al. (2017) suggest that increasing the degree of anthropomorphism may increase attribution of intentionality to intelligent agents such as a chatbot, attributing a human mind to the non-human entity. In particular, human-like facial features embedded in the chatbot may signal internal mental states, such as positive or negative intentions (Wiese et al. 2017). This could encourage human-like social connections (van Doorn et al. 2017).

In the present study, we adapt and apply the BIAF framework to AI-based chatbots to investigate how perceived intentionality, spanning both intentions and ability dimensions, affects the way individuals interact with them. The more a chatbot is perceived as a psychological entity endowed with internal states, the more users believe it is able to have and implement its intentions (MacInnis and Folkes 2017; van Doorn et al. 2017). By attributing intentions to objects, consumers interact with them as if they had human-like minds (MacInnis and Folkes 2017). This effect should be strengthened when the chatbot has anthropomorphic visual cues (Go and Sundar 2019; van Doorn et al. 2017). In fact, human-like perceptions should make users perceive the chatbot as “a person” with mental states and its own intentions (Go and Sundar 2019).

3.1.3. Intentionality and Coping Strategies

According to Sundar (2008), interface cues shape user perceptions, by triggering cognitive heuristics about the nature and substance of the interaction. If people presume the agent with which they are interacting is a chatbot, they likely evaluate the quality of its performance according to their preexisting perceptions of chatbots. Anthropomorphic visual cues instead predispose users to evaluate the agent's performance on the basis of their expectations about humans. Attributing human-like visual cues to an agent may trigger heuristics related to human interactions, which could improve the perception of the agent (Go and Sundar 2019). In particular, when customers attribute stronger mental states to an object, they are more likely to apply human schema and accordingly respond as they would to a human agent (Golossenko et al. 2020). In this regard, research shows that consumers seem to prefer interactions with brands that are anthropomorphized, even though they are unaware of this (MacInnis and Folkes 2017). Attributing anthropomorphic visual cues also affect how wrong people feel it is to harm inanimate objects (Waytz et al. 2010). When attributing human mental capacities, such as intentions and feelings, to the object, individuals tend to treat the object like a human (MacInnis and Folkes 2017; Waytz et al. 2010). Moreover, just as individuals have social norms that guide their relationships with other humans, they also appear to have norms that guide their relationships with non-human entities. For instance, according to CASA theory, when interacting with computers people applies social rules to machines, just as they do with humans (Nass and Moon 2000). This phenomenon is even stronger when machines present human-like characteristics. In this regard, human-like facial features embedded in the chatbot may signal internal mental states, such as positive or negative intentions (Wiese et al. 2017). Attributing intentions to the chatbot may facilitate the activation of human schema (Go and Sundar 2019; MacInnis and Folkes 2017), triggering coping behaviors that normally consumers adopt when interacting with another human. For instance, in the context of service failure, consumers may adopt confrontive coping strategies with a human-like chatbot as they would do with a human agent to vent their negative emotions caused by the poor service performance. Thus, we propose that the effect of perceived intentionality on confrontive coping should be strengthened when the chatbot has anthropomorphic visual cues (Go and Sundar 2019; van Doorn et al. 2017). In fact, human-like characteristics should make users perceive the chatbot as "a person" with mental states and intentions, triggering the activation of human schema (Go and Sundar 2019; MacInnis and Folkes 2017). Thus, we propose:

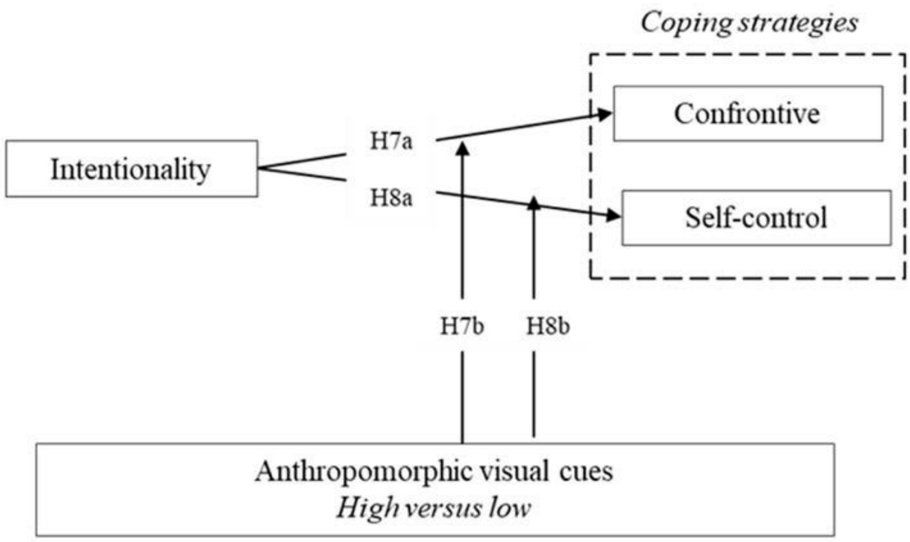
H7: Intentionality (a) has a positive effect on confrontive coping, (b) moderated by chatbot anthropomorphic visual cues, such that at high levels of anthropomorphic visual cues, intentionality has a stronger positive effect than at low levels.

When a chatbot has anthropomorphic visual cues, evoking human-like characteristics and internal states, consumers might also try to exert more self-control. In this regard, expressing emotions provides a venting function; controlling emotions represents adherence to social norms, which also should apply in interactions with an anthropomorphic chatbot for which the consumer perceives a presence of mind and intentions (Belanche et al. 2020; Carruthers and Smith 1996). In fact, exerting self-control allows individuals to override undesirable responses, behaving in a more flexible way and applying social norms. Greater anthropomorphic visual cues should increase perceptions that the machine is endowed with cognition (Golossenko et al. 2020, Gray et al. 207, van Doorn et al. 2017), which then may enhance self-control. Indeed, emotion-regulating norms implicitly activated by social cues can lead to automatic emotion control (Mauss et al. 2007). We propose that anthropomorphic visual cues can be considered as a social cue that implicitly leads to self-control when interacting with chatbots. Thus:

H8: Intentionality (a) has a positive effect on self-control, (b) moderated by chatbot anthropomorphic visual cues, such that at high levels of anthropomorphic visual cues, intentionality has a stronger positive effect than at low levels.

Figure 12 shows the hypotheses formalized in the conceptual model.

Figure 12 Conceptual model of Study 2



3.2. Methodology

3.2.1. Experimental Design

In the second study, we examine chatbots with different levels of anthropomorphic visual cues. Therefore, drawing from Cyr et al. (2009) and Go and Sundar (2019) we perform a between-subjects design where the level of anthropomorphic visual cues of the chatbot (low versus high) is manipulated. We depict the online chatbot in the high anthropomorphic visual cues condition as a human person (Figure 13), whereas the depiction in the low anthropomorphic condition features a robot-like device (Figure 14). We use highly realistic, human-like, computer-generated facial images instead of pictures of real humans, presenting a neutral emotional expression (no smile) to avoid the risk of emotional contagion (Hatfield et al. 2014). To select the picture used in the high anthropomorphic visual cues condition, we gather four pictures of human-like computer-generated agents, and then ask 20 international Master's students to rate the resemblance to humans on a scale from 1 (strongly disagree) to 7 (strongly agree) ("The agent looks like a real human"). We select the picture that was considered more human-like (M = 6.350, SD = .671). We draw from Go and Sundar (2019) to select the image for the condition with low anthropomorphic visual cues by using an image of a robot. Participants are continuously exposed to the manipulation of the chatbot's visual cue during the interaction (Go and Sundar 2019). As in Study 1, we also named the chatbot. Unlike in Study 1, we do not manipulate the identity cues. Thus, in both conditions, the chatbot introduces itself in the same way (“Hello, I am Marc. I am the airline chatbot”).

Figure 13 Sample stimulus of the video depicting interaction with the chatbot in the high anthropomorphic condition

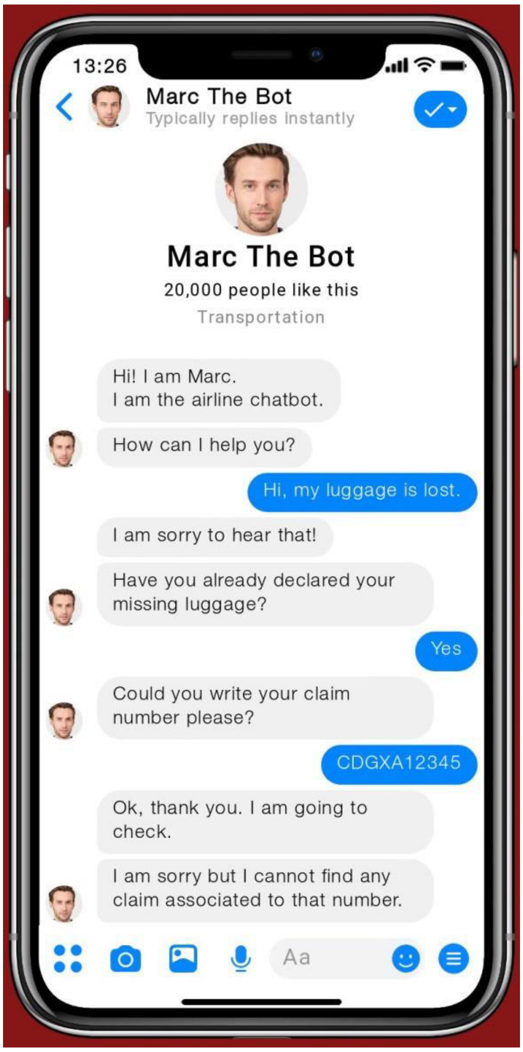
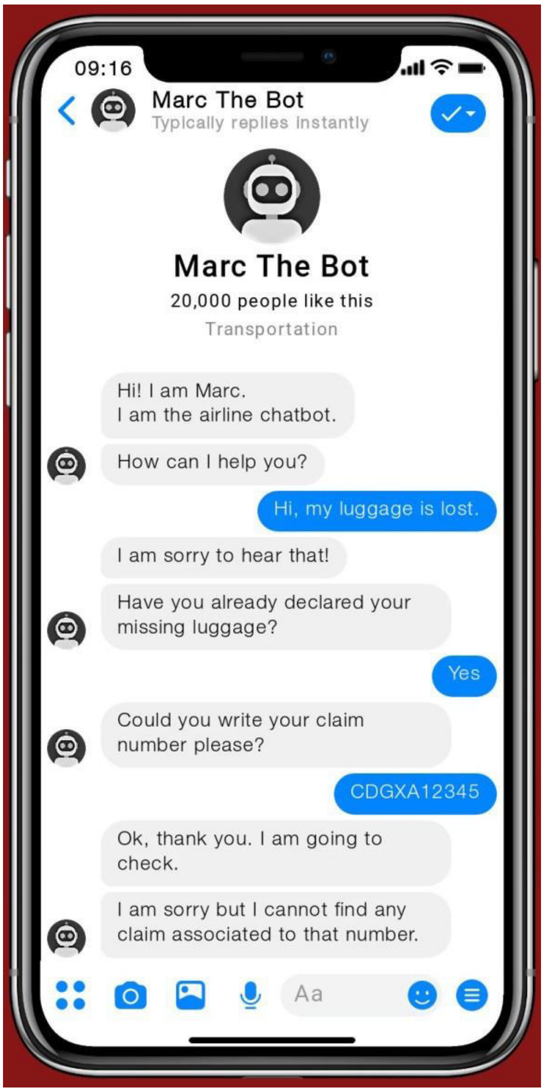


Figure 14 Sample stimulus of the video depicting interaction with the chatbot in the low anthropomorphic condition



We use the same scenario of a service failure in the airline setting and the same procedures that we use in Study 1 (see Appendix 1 for the description of the service failure; see Appendix 2 for the script of the interaction shown in the video). As in study 1, we evaluate and confirm the realism of the scenarios adapting the scale from Bagozzi et al. (2016): “The scenario is realistic”; “The scenario is believable”; “It was easy for me to put myself in the situation of the customer.” Items are measured on a scale from 1 “strongly disagree” to 7 “strongly agree”. The three items indicate our experiment offers an ecologically valid setting (M=5.975; SD=.895). The questionnaire has been translated from English to French using double-back translation (Brislin 1980).

We also include two attention checks. The first, placed right after the video showing the service failure delivered by the chatbot ask participants to mark, as true or false, the statement, “In the video, the chatbot manages to solve the customer's problem”. Only participants who answered “false” are allowed to continue the study. The second attention check appear in the middle of the survey and instruct participants to indicate a specific response (“Please respond with ‘disagree’ for this item”) (Meade and Craig 2012). All the participants included in the final sample correctly completed the attention checks.

3.2.2. Sample

The experiment is conducted online with the assistance of a professional panel provider who administer the questionnaire to a sample of its members (N = 120). The data are collected in October 2020. Participants are randomly assigned to one of the two conditions (high anthropomorphic visual cues; low anthropomorphic visual cues). Each group have 60 participants. We implement quotas to ensure a representative sample for each condition, according to the French population census of 2019 (Table 25).

Table 25 Sample description of Study 2

		Gender		**Total**
		Women	**Men**	
Age	18-29	10	10	20
	30-39	10	10	20
	40-49	10	10	20
	50-59	10	10	20
	60-69	10	8	18
	> 70	12	10	22
Total		62	58	120

3.2.3. Measurement Scales

We measure confrontive coping adapting the scale from Yi and Baumgartner (2004), self-control from Yi and Baumgartner (2004) and Folkman et al. (1986) and intentionality from Kervyn et al. (2012). For the manipulation check, we measure anthropomorphic visual cues adapting the scale from Go and Sundar (2019). All scales are measured on a Likert scale from 1 (strongly disagree) to 7 (strongly agree). We drop items with factor loadings less than .7 (Hair et al. 2013) (Table 26). All the loadings are significant at .001. The factor loadings exceed the cross-loadings, and the square roots of the AVEs are greater than the cross-correlations (Table 27). We thus have evidence of convergent and discriminant validity. The model fit is acceptable with $Chi^2/DF < 5$ (Byrne 2006), CFI >.80 (Bentler 1990), TLI > .80 (Bentler and Bonett 1980) (Table 28). The RMSEA value is a little too high. Browne and Cudeck (1992) suggest RMSEA <.05 as close fit and values beyond .10 as poor. To avoid response order effects, we randomize the order of the measures in the questionnaire (Schuman and Presser 1996).

Table 26 Reliability and convergent validity of Study 2

	SE	***p***
Confrontive (Yi and Baumgartner 2004) α=.833, AVE=.746		
I would have let the chatbot know how angry/frustrated I was.[b]	.554	< .001
I would have argued my case.[b]	.198	>.05
I would have continued to interact with the chatbot to complain about the situation.	.803	< .001
I would have talked more with the customer service employee/chatbot about the problem to ask to correct it.	.827	< .001
I would have tried to get the customer service employee/chatbot to change his/her mind.	.813	< .001
Self-control (Yi and Baumgartner 2004; Folkman et al. 1986) α=.880, AVE=.849		
I would have tried to keep my negative feelings to myself.	.726	< .001

I would have kept others from knowing how bad the service is. [b]	.308	< .001
I would have tried not to act too hastily or follow my first hunch.	.887	< .001
I would have tried to keep my negative feelings from interfering.	.947	< .001
Intentionality (Kervyin et al. 2012) α=.921, AVE=.755		
This chatbot has good intentions toward the user.	.843	< .001
This chatbot consistently acts with the user's best interests in mind.	.971	< .001
This chatbot has the ability to implement its intentions.	.854	< .001
This chatbot is effective at achieving its goal.	.800	< .001
Manipulation check: Anthropomorphic visual cues (Go and Sundar 2019) α=.857, AVE=2.709		
The chatbot profile picture looks very human-like.	2.512	>.05
The chatbot profile picture looks very machine-like (r)	.299	>.05

[b]items dropped

Table 27 Discriminant validity, Study 2

Construct Scale	Descriptives		Correlations			
	M	SD	1	2	3	4
1. Anthropomorphic visual cues	-	-	**1**			
2. Intentionality	4.127	1.442	-.022	**.869**		
3. Confrontive	4.039	1.362	-.023	.189*	**.742**	
4. Self-control	4.108	1.383	.083	.479**	-.013	**.858**

Scales range from 1 (low values) to 7 (high values of the respective variable). Only the variable "anthropomorphic visual cues" is a dummy variable (1 = high anthropomorphic visual cues, 2 = low anthropomorphic visual cues). The AVEs' (average variance extracted) square roots are presented in bold characters

Table 28 Model fit indices

χ^2	df	RMSEA	CFI	TLI
101	48	.09	.94	.92

3.3. Results

3.3.1. Manipulation Check

An independent sample t-test shows that participants in the high anthropomorphic condition perceive the chatbot as significantly ($t = 9.178$, $p < .001$) more human-like ($M = 5.216$, $SD = 1.226$) than those in the low anthropomorphic condition ($M = 2.908$, $SD = 1.514$). Thus, we confirm the validity of the manipulation of the scenarios.

3.3.2. Effect of Intentionality on Coping Strategies

We conduct a moderation analysis with the Process macro for SPSS model 1 (Hayes 2018). Intentionality has a significant effect on confrontive coping ($b = 1.192$, $SE = .292$, $t = 4.083$, $p < .001$), as we predicted in H7a, and it is significantly moderated by chatbot anthropomorphic visual cues ($b = -.717$; $SE = .183$, $t = -3.911$, $p < .01$), as we noted with H7b (Table 29). In the high anthropomorphic condition, intentionality has significant effect on confrontive coping ($b = .398$; $SE = .155$, $t = 2.569$, $p < .05$), but at a low level of anthropomorphic visual cues, intentionality does not have a significant effect ($b = -.128$, $SE = .147$, $t = -.871$, $p > .05$). In support of H8a, intentionality also has a significant positive effect on self-control ($b = .558$, $SE = .247$, $t = 2.256$, $p < .05$). Nevertheless, chatbot anthropomorphic visual cues do not significantly moderate the relationship ($b = -.063$, $SE = .155$, $t = -.410$, $p > .05$), in contrast with H8b. In fact, we find a significant positive effect of intentionality on self-control in both anthropomorphic conditions (high $b = .494$, $SE = .111$, $t = 4.447$, $p < .001$; low $b = .430$, $SE = .108$, $t = 3.967$, $p < .001$).

Table 29 Intentionality, coping strategies and anthropomorphic visual cues

	b	SE	*t*	*p*	R^2	Hypothesis
Intentionality → confrontive	1.192	.292	4.083	<.001	.127	H7a:supported

Intentionality * anthropomorphic visual cues → confrontive	-.717	.183	-3.911	<.01		H7b: supported
Intentionality → self-control	.558	.247	2.256	<.05	.239	H8a: supported
Intentionality * anthropomorphic visual cues → self-control	-.063	.155	-.410	>.05		H8b: not supported

3.4. Discussion

As in Study 1, we find that participants engage in confrontations with the chatbot to manage their negative emotions. We extend previous results showing that when customers attribute intentions and the ability to act on them to a chatbot, they are more willing to engage in confrontation with the machine, arguing their cases and looking for a solution. This effect is moderated by the anthropomorphic visual cues: the more the chatbot resembles a human, the more the perceived intentionality influences the confrontation. Thus, the attribution of social cognitive abilities to AI-based chatbots, namely the attributions of intention and ability to implement them, promotes the activation of problem-oriented strategies. Moreover, our results support previous research showing that individuals tend to apply social norms to machines and show their emotions to them (Nass and Moon 2000). We also extend this finding by showing that perceived social cognitive abilities attributed to the machine help explain these behaviors (Angeli and Brauman 2008; Fiske et al. 2007; Kervyin et al. 2012). Consistent with a growing stream of research, the attribution of human-like traits promotes the activation of human schemas (Go and Sundar 2019; van Doorn et al. 2017).

Concerning self-control, results suggest that intentionality also positively affects self-control. Thus, the more the chatbot is perceived as having cognition, the more individuals tend to control their emotions. Participants try to avoid acting impulsively in their interactions across anthropomorphic conditions. As prior literature suggests, people can experience both problem-focused and emotions-focused coping strategies simultaneously (Folkman and

Lazarus 1990). Our results support these findings, showing that, also when interacting with intelligent machines, individuals may engage simultaneously in problem-focused and emotions-focused coping strategies.

4. Study 3: Human-Chatbot Interactions, Anthropomorphic Visual Cues and Attributions of Responsibility

In the first study we show that when consumers interact with chatbots, they tend to attribute significantly higher responsibility for service failure to the company compared to when they interact with humans, feeling more frustrated about the situation. This result confirms recent findings suggesting that bots can be perceived as less responsible due to the lack of control over their actions (Leo and Huh 2020). Furthermore, we argue that this effect could be caused by the chatbot's lack of intentions, which cannot be directly considered as responsible for the negative outcome. For this reason, the attribution of responsibility to the company is higher. If, on the one hand, research confirms the potential negative effect that AI-based service failure can have on the company (Belanche et al. 2020; Leo and Huh 2020), on the other hand we still need to understand how to mitigate these effects. To address this research gap we extend the research framework further, by investigating how attributions of responsibility to the company change according to different levels of anthropomorphic visual cues and according to the perceived intentionality. We suggest that, increasing the perceived intentionality of the chatbot through higher anthropomorphic visual cues might help to decrease the negative attributions to the company.

4.1. Literature Review and Hypotheses Development

When an AI-based agent is perceived as a psychological entity, endowed with human characteristics consumers' causal attributions toward that agent should grow stronger

(Varela-Neira et al. 2014). In fact, because the agent is perceived to have intentions and abilities to implement them, it could also be easier for customers to attribute fault to the chatbot (Gray and Wegner 2012). In addition, the more the chatbot resembles a human, the more consumers apply human heuristics to the interaction (Go and Sundar 2009), including one that holds agents accountable for their actions (van Doorn et al. 2017).

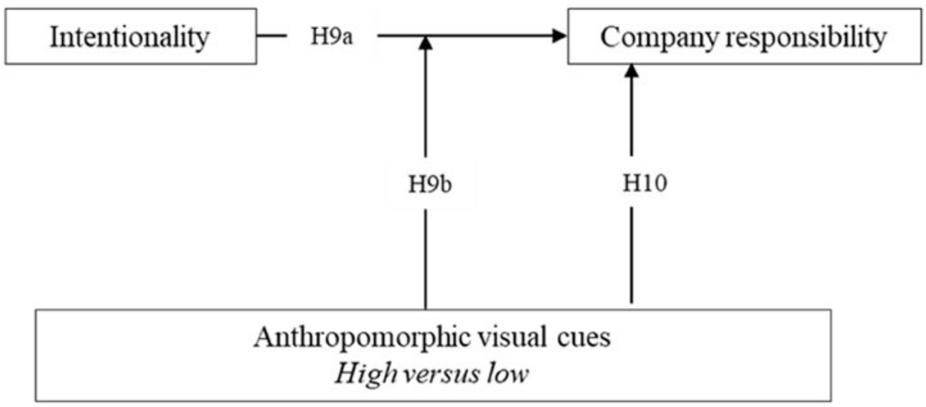
Anthropomorphic visual cues can also increase perceived intentions and ability (Fournier and Alvarez 2012; Kim et al. 2019; Waytz et al. 2014). For instance, in their investigation of AI-based autonomous vehicles, Epley et al. (2018) suggest that people tend to attribute more responsibilities to anthropomorphized intelligent cars for accidents than they do to less anthropomorphized vehicles. Because higher levels of anthropomorphic visual cues boost the sense that non-human actors are psychological entities (van Doorn et al. 2017), we posit that customers apply human heuristics (Go and Sundar 2019. In particular, the more the AI-based chatbot has anthropomorphic visual cues and is perceived as having intentions, the more it may be considered responsible for the failure. Mental qualities, such as intentions and cognition, explain behaviors, so they also might provide evident reasons for why an object has acted in a certain way, including actions that lead to negative outcomes (Gossolenko et al. 2020; Puzakova et al. 2013). In this case, the company might appear to be less responsible for the poor service, as the chatbot would be perceived as having sufficient cognitive capabilities to be held fully responsible for the negative outcome. This effect should be stronger when the chatbot has high levels of anthropomorphic visual cues (Go and Sundar 2019). In fact, the more it resembles a human, the more individuals activate human heuristics, potentially perceiving the chatbot as responsible rather than the company. On the other hand, when the chatbot has low anthropomorphic visual cues, it is less perceived as a real social entity with cognition (Epley et al. 2018). In this case the negative relationship of intentionality and attributions to the company would be weaker, as the company might be perceived as more responsible. Thus:

H9: Intentionality (a) has a negative effect on attributions of responsibility to the company, (b) moderated by the level of anthropomorphic visual cues of the chatbot, such that intentionality has a stronger negative effect on these attributions at high rather than low levels of anthropomorphic visual cues.

H10: Anthropomorphic visual cues have a negative direct effect on attributions of responsibility to the company.

Figure 15 shows the hypotheses formalized in the conceptual model.

Figure 15 Conceptual model of Study 3



4.2. Methodology

4.2.1. Experimental Design

With a between-subjects experimental design, we manipulate the level of anthropomorphic visual cues: (low versus high). To select the picture used in the condition with high anthropomorphic visual cues, 20 international Master's students rated four images of human-like computer-generated agents ("The agent looks like a real person") on a scale of 1 (strongly disagree) to 7 (strongly agree). Thus, for the high anthropomorphic visual cues condition, we selected the picture which is considered more human-like (M = 6.20; SD = .834). For the selection of the image for the low anthropomorphic condition, we draw from Go and Sundar (2019), using a picture of a robot.

We conduct the experiment using the same procedure of Study 1 and Study 2: firstly, participants read a description of the service failure (Appendix 1); next, participants watched a short video showing an interaction with the chatbot: a chatbot with high levels of anthropomorphic visual cues in Group 1 (Figure 16) and a chatbot with low levels of anthropomorphic visual cues in Group 2 (Figure 17). The script of the interaction is show in the Appendix 2. During the interaction, participants were continuously exposed to the manipulation of the chatbot's visual cue (Go and Sundar 2019). As in Study 2, we do not manipulate the identity of the agent: the chatbot presents itself as an "airline chatbot" in both conditions. As in Study 2, we evaluate the realism of the scenario on a seven-point Likert scale drawing from Bagozzi et al. (2016). Results confirm the realism of the scenario (M = 5.716, SD = 1.391). The questionnaire was pretested with 35 international master's students who speak fluent English. We also include two attention checks, using the same items of Study 2. All the participants included in the final sample correctly completed the attention checks.

Figure 16 Sample stimulus of the video depicting interaction with the chatbot in the high anthropomorphic condition

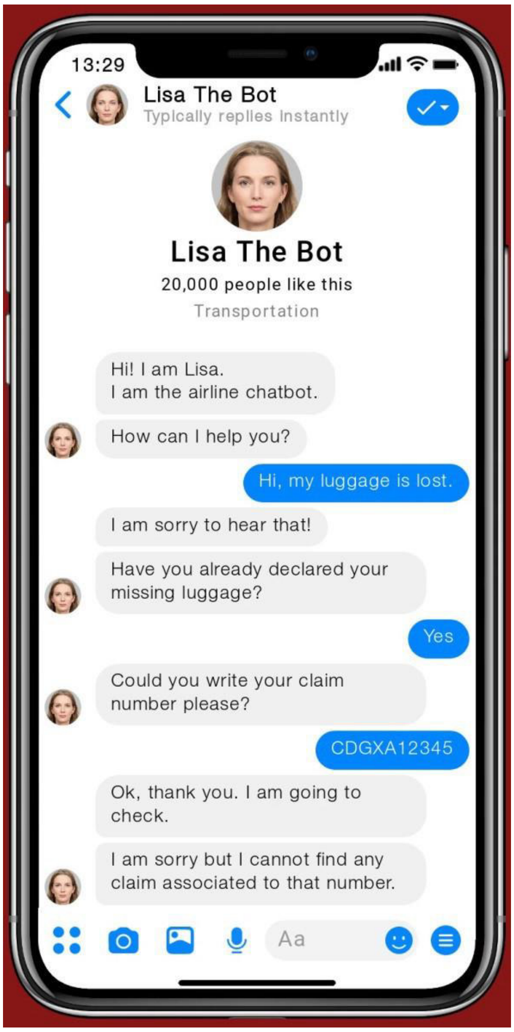
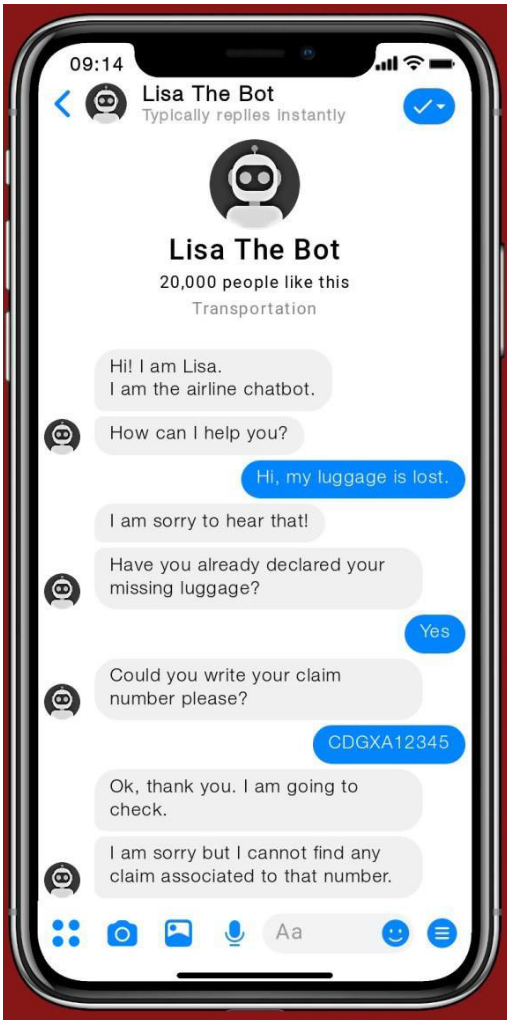


Figure 17 Sample stimulus of the video depicting interaction with the chatbot in the low anthropomorphic condition



4.2.2. Sample

We administer the questionnaire online, with the help of a professional panel provider, to a U.S. sample (N = 120). Each group includes 60 randomly assigned participants. We also implement quotas to ensure representative samples, according to the U.S. Census 2019. Age and gender distributions are presented in Table 30.

Table 30 Sample description of Study 3

		GENDER		Total
		Women	**Men**	
Age	18-29	15	11	26
	30-39	10	10	20

40-49	10	10	20
50-59	10	9	19
60-69	10	8	18
>70	10	7	17
Total	65	55	120

4.2.3. Measurement Scales

We use the measurement scale of intentionality (Kervyn et al. 2012) and anthropomorphic visual cues (Go and Sundar 2019) from Study 2. We adapt the scales for attribution of responsibility to the company (Gelbrich 2010) from Study 1. We again keep only those items with factor loadings greater than .7 (Hair et al. 2013). All factor loadings are significant at the .001 level (Table 31). Factor loadings exceed the cross-loadings and the square roots of AVEs are greater than cross-correlations (Table 32). We thus find support for convergent and discriminant validity (Hair et al. 2013). The model fit is acceptable with Chi²/DF < 5 (Byrne 2006), CFI >.80 (Bentler 1990), TLI > .80 (Bentler and Bonett 1980) and RMSEA = .08 close to the standard suggested by Browne and Cudeck (1992) (Table 33)

Table 31 Reliability and convergent validity of Study 3

	SE	***p***
Firm responsibility (Gelbrich 2010) α=.918, AVE=.864		
The airline is responsible for this service failure.	.838	< .001
The problem encountered is all the fault of the airline.	1.013	< .001
Intentionality (Kervyin et al. 2012) α=.894 AVE=.687		
This chatbot has good intentions toward the user.	.853	< .001
This chatbot consistently acts with the user's best interests in mind.	.896	< .001
This chatbot has the ability to implement its intentions.	.829	< .001
This chatbot is effective at achieving its goal.	.727	< .001
Manipulation check: Anthropomorphic visual cues (Go and Sundar 2019) α=.657 AVE=.500		

The chatbot profile picture looks very human-like.	.751	<.001
The chatbot profile picture looks very machine-like (r)	.654	<.001

Table 32 Discriminant validity, Study 3

	Descriptives		Correlations		
	M	**SD**	**1**	**2**	**3**
1. Anthropomorphic visual cues	-	-	**1**		
2. Intentionality	3.862	1.563	.070	**.829**	
3. Company responsibility	5.87	1.371	-.095	-.179*	**.930**

Scales range from 1 (low values) to 7 (high values of the respective variable). Only the variable "anthropomorphic visual cues" is a dummy variable (1 = high anthropomorphic visual cues, 2 = low anthropomorphic visual cues). The AVEs' (average variance extracted) square roots are presented in bold characters.

Table 33 Model fit indices

χ^2	df	RMSEA	CFI	TLI
31.5	17	.08	.97	.95

4.3. Results

4.3.1. Manipulation Check

The results of an independent sample t-test confirm that participants in the high anthropomorphic condition perceive the chatbot to be more human-like (M = 4.558, SD = 1.639) than those in the low anthropomorphic condition (M = 2.775, SD = 1.563; t = 6.098, $p < .001$). Thus, we confirm the validity of the manipulation of the scenarios.

4.3.2. Intentionality, Attributions of Responsibility and Anthropomorphic Visual Cues

The results of the moderation analysis conducted using the Process macro for SPSS model 1 (Hayes 2018), shows that intentionality has a significant negative effect on attributions of responsibility to the company (b = -.576, SE = .246, t = -2.337, $p < .05$). Thus, H9a is supported. However, we do not find a significant moderating effect of anthropomorphic visual cues on the relationship between intentionality and attributions of responsibility to the company (b=.143, SE=.079, t=1.815, p>.05). Thus, H9b is not supported. Nevertheless, we find that anthropomorphic visual cues have a significant negative direct effect on attribution of responsibility to the company (b=-.667, SE=.329, t=-2.026, p<.05). Thus, H10 is supported. Results are show in Table 34.

Table 34 Effects of anthropomorphic visual cues, Study 3

	b	**SE**	**t**	***p***	**R^2**	**Hypothesis**
Intentionality → company responsibility	-.576	.246	-2.337	<.05	.065	H9a: supported
Intentionality * anthropomorphic visual cues → company responsibility	.143	.079	1.815	>.05		H9b: not supported
Anthropomorphic visual cues → company responsibility	-.667	.329	-2.026	<.05		H10: supported

4.4. Discussion

The results of Study 3 suggest that the lack of perceived intentionality influences the stronger attributions of responsibility to the company. When customers do not infer social cognition onto the chatbot and perceive it as non-intentional, they do not consider it as responsible for the negative outcome. In this case, the firm will bear higher responsibility for the service failure (Belanche et al. 2020; Leo and Huh 2020). Despite we do not find a significant moderating effect of anthropomorphic visual cues on the relationship between intentionality and attributions to the company, results suggest that anthropomorphic visual cues directly affect attributions of responsibility to the firm. Specifically, the more the chatbot exhibits human-like characteristics, the less the company is held responsible for the negative outcome. In this context, previous studies have suggested that chatbots with human-like cues can have a positive effect on relationship built with the company, for example, by increasing emotional attachment to the firm and developing stronger relationships (Araujo 2018). Our results extend previous research showing that anthropomorphic visual cues can also have beneficial effects in the customer-company relationships by decreasing the attributions of responsibility to the company in case of failures in the context of AI-based services.

5. General Discussion

Our first study suggests that when individuals interact with an AI-based chatbot in the context of service failure, blame attributions differ when they are aware of interacting with a chatbot rather than a human agent. This result is in line with recent research showing that customers attribute higher responsibilities to the firm rather than the frontline service robot (Belanche et al. 2020). In the third experiment we extend this result, suggesting that individuals blame less the AI-based chatbot due to the lack of perceived intentionality of the machine (Gray and Wegner 2012; Lee 2018). In this respect, as the chatbot is perceived as not having intentions and control over them, it is not considered as responsible (Leo and Huh 2020). Thus, the less the agent is perceived as having intentions, the less is responsible for the negative outcome. In this case the company bears more responsibility for the poor service performance. In addition, we suggest that anthropomorphic visual cues may decrease the attribution of responsibility to the company. Attributing human-like characteristics to the agent may help create a sense of human connection, making consumers feel that they are interacting with a social entity endowed with cognition (Choi et al. 2021; van Doorn et al. 2017). In this regard, research highlights the pivotal role of human-like touch in service contests, which can be especially relevant in situations which may involve failure handling (Choi et al. 2021; Larivière et al. 2017). As our studies suggest, increasing anthropomorphism by adding anthropomorphic visual cues can be a strategy to decrease negative attributions to the company in case of service failure.

By comparing human-human and human-chatbot interactions, our first experiment also suggests that, when interacting with AI-based chatbots, on the one hand customers experience higher frustration about the negative situation they cannot control, due to the attribution of responsibility to the company (Roseman 1991, Gelbrich 2010). On the other hand, when interacting with human agents, the attribution of responsibility includes the employees and the company, increasing customers' anger toward the human agent blamed for the poor service (Bonifield and Cole 2007; Gelbrich 2010). Consistently, research suggests that if people attribute responsibility for a negative event to another person and perceive that the other could have prevented the event's occurrence, they respond with anger (Su et al. 2018). In this case, anger is characterized by a disposition to attack the perpetrator of the negative event in order to punish the person or obtain redress (Beaudry and Pinsonneault 2010; Su et al. 2018). However, when individuals attribute the event to external factors, they may experience frustration about the situation (Gelbrich 2010). In the case of AI-based service factor, as the chatbot is not directly accountable for the outcome, the company's decision of implementing such a machine may be considered as the cause of the accident. Thus, even if participants experience negative emotions in both conditions, their emotional responses differ when interacting with a human and a chatbot, according to their attributions of responsibility. In contrast, their coping strategies are similar; they adopt confrontive coping strategies in both human–human and human–chatbot service failures. Despite being aware of interacting with a chatbot, respondents still vent their negative emotions as they would to a human agent, arguing their case, and asking for solutions. This result is in line with previous research showing that individuals tend to apply social norms to interaction with machines, which may even involve feelings of hostility and attacking the machine in case of negative outcome (Angeli and Brahnam 2008; Nass and Moon 2000).

In the second experiment, we confirm and extend the results from Study 1, showing that the perception of the communication partner as being able to plan and implement his or her own intentions, influences the use of confrontational coping strategies. Moreover, this effect is stronger when the agent is highly anthropomorphized. This result is consistent with the literature showing that the more the agent is anthropomorphized, the more individuals activate human schemas in the interaction (Go and Sundar, 2019; Golossenko et al. 2020). However, we enrich the existent literature showing that anthropomorphizing the chatbot might foster problem-focused coping strategies. On the one hand, participants report engaging in a confrontation with the chatbot to cope with their negative emotions, arguing their cases and looking for solutions; on the other hand, however, they declare to self-control their negative emotions to avoid acting too impulsively when interacting with a chatbot, under both high and low anthropomorphic conditions. Previous research has shown that people can use both types of coping in virtually any type of stressful situation (Folkman and Lazarus 1986). In this regard, Liang et al. (2019) show that individuals cope with IT related threats through both emotion-focused and problem-focused strategies. In particular, in our studies coping has two main functions: confrontational coping is used to deal with the problem that is causing the stress (problem-focused coping); self-control is used to regulate and control emotions (emotion-focused coping). Indeed, social psychology suggests that 'self-control', associated with 'self-regulation,' 'impulse control,' 'cognitive control', is often related to prosocial behaviors, inhibiting aggressive behaviors (DeWall et al. 2011). Thus, on the one hand, the more the chatbot is perceived as endowed with mental states and it resembles a human, the more consumers might use problem-focused strategies by engaging in confrontive coping. On the other hand, regardless of the chatbots anthropomorphic visual cues, individuals tend to use emotion-focused strategies when faced with AI-based service failures, controlling their emotions. Thus, we propose that attributing human-like characteristics can be a good solution to foster both problem-focused coping, useful to handle the service failure, and emotion-focused coping, which help consumers to restore emotional balance disrupted by the negative event.

6. Theoretical Contributions

Our research offers three main contributions to the theory. Firstly, we contribute to the emerging literature of AI-based service and to consumer behavior theories (Davenport et al. 2020; Huang and Rust 2018; Meyer-Waarden et al. 2020; Wirtz et al. 2018). In particular, we enrich the literature investigating consumers' interaction with AI-based agents in the context of service failure and double deviations, adopting the well-established framework of Cognitive Appraisal Theory of Emotions (Belanche et al. 2020; Choi et al. 2021; Roseman 1991). In this regard, we show for the first time how according to human-human to human-chatbot interactions, on the one hand customers differently experience emotions in failing AI-based service settings; on the other hand, they tend to adopt similar coping strategies to regulate their emotional responses. In this way, we also contribute to the CASA theory (computers as social actors; Nass and Moon 2000) suggesting that customers tend to adopt confrontive coping strategies even when interacting with an AI based chatbot thus applying social rules also in case of negative situations. In addition, we show the determinants of such behaviors, namely perceptions of intentions and ability, integrating for the first time the BIAF framework in the investigations of consumers' social perceptions of AI-based service (Kervyin et al. 2012).

Finally, we contribute to Attribution Theory (Weiner 2000) by shedding light on how attributions of responsibility toward service agents and firms change depending on the identity of the service providers, namely humans compared to AI based chatbot agents. We offer new insights highlighting how the agent characteristics, in particular the anthropomorphic visual cues, might affect consumers' attributions of responsibility (Aggarwal and McGill 2007; Araujo 2018; Blut et al. 2021; Epley et al. 2018; Go and Sundar 2019; Lee 2010).

7. Managerial Implications

Integrating an AI-based chatbot in service settings, in particular to handle complex failures such as in the context of double deviation, can have negative repercussions for the firm. In fact, our studies suggest that customers tend to attribute more responsibility to the firm when they interact with a chatbot. In turn, their anger and frustration, manifested in confrontive coping strategies, predominantly target the firm. We suggest that anthropomorphizing the chatbot with human-like visual cues, in particular a face and a name could reduce attribution of responsibility to the organization and promote both problem-focused and emotion-focused coping strategies. In particular, problem-focused coping can be useful to handle the service failure looking for solutions, whilst emotion-focused coping help consumers to cope with the negative emotions caused by the negative event, restoring the emotional balance disrupted by the event. Thus, creating a sense of human connection, so that consumers believe they are in the presence of another social entity that might assist and understand them (van Doorn et al. 2017) may play a key role to mitigate negative attributions and help consumers to deal with the situation.

Our studies also show that consumers might experience strong negative emotions when interacting with an AI-based chatbot. Therefore, we suggest that companies need to find a way to actively deal with customers' negative emotional reactions. This is because chatbots are still at the mechanical and analytical level of intelligence, lacking intuition and empathy

(Huang and Rust 2018). Thus, we suggest that companies need to find the optimal balance between "tech" and "touch" in service encounters (Giebelhausen et al. 2014). Current technology might not be able to evoke perceptions of empathy yet (Davenport et al. 2020), so service managers should assign human agents to deal with complex negative emotional reactions. Managers must arbitrate between strong competitive advantages delivered by well-trained human service providers and the lower costs of AI-based chatbots (Huang and Rust 2018). For this reason, it is important to consider both the efficiency and the competences of AI-based chatbots in terms of meeting customers' expectations according to the context (Meyer-Waarden et al. 2020).

8. Limitations and Further Research Directions

The experimental design of our three studies means that we cannot test the focal interactions in real-world conditions. Further research might investigate interactions with AI-based chatbots in actual service failures, for instance by using field studies.

In addition, we only investigate a double deviation situation in the airline context. So, the results cannot be generalized to other service contexts. For this reason, we suggest that further research should also address other service industries, such as healthcare or banking services. In these contexts, the ethical consideration of implementing AI-based chatbots to deal with sensitive information also might be influential and should be investigated more closely (Murtarelli et al. 2021). In addition, our study suggests that users may experience negative emotions when interacting with AI-based chatbots. However, we focus only on two specific emotions, anger and frustration. Further research could extend our research framework, investigating other emotional reactions such as anxiety or fear, and other coping strategies to regulate negative emotions, such as denial and psychological distancing (Liang et al. 2019). Moreover, considering the negative emotional reactions, the potential consequences for consumers' well-being and satisfaction should be further investigated.

We also suggest extending our research framework to specify boundary conditions, such as those related to the conversational styles or personality traits exhibited by chatbots. For instance, attribution of personality may also be a form of anthropomorphism (Kim and McGill 2011, Golossenko et al. 2020). In this regard, research on human–computer interactions reveals that people tend to adapt their responses to computers according to the design of its personality (Nass and Moon 2000). Because AI-based chatbots are able to engage in human-like conversation, their personality might be especially salient and even encourage relationships with users (van Doorn et al. 2017).

9. Towards the Next Chapter: Autonomous Cars

Conversational agents represent a great opportunity to investigate the way consumers communicate and verbally interact with new AI technologies which mainly use ML and NLP emulating human-human interaction. However, when looking into consumer behaviors related to AI, it is fundamental to take into account the vast range of AI applications and techniques. In this regard, besides the conversational agents, other technological innovations, even more disruptive and uncertain, are rising important questions concerning the way they need to enter the market and the consequences they might have for society. Driverless cars are one of the most well-known examples. By using computer visions and deep learning algorithms they are able to deliver a different type of service to consumers: the driving tasks. Many companies are working to make autonomous vehicles safer and more efficient. In 2019, we already had some examples of robo-taxi implemented in Phoenix, Arizona (Hecht 2018). However, the technology is not fully mature, as many companies are still developing the levels of automation and gradually implementing autonomous functions. In addition, the way individuals are going to adopt and use this type of technology still raises many questions which need to be addressed. For this reason, in the third chapter, we use autonomous cars as units of analysis, which give us the opportunity to investigate another aspect of AI different from the verbal interaction investigated in chapter 2: the usage and the experience with different levels of AI in critical situations such as driving.

Introduction

PART I
Defining AI in Marketing

Chapter 1. Artificial Intelligence in Marketing Research: Scientometric, TCCM Review and a Research Agenda

PART II
Practical AI Applications

Chapter 2. Rage Against the Machine: Investigating Consumers Negative Emotions, Attributions of Responsibility and Coping Strategies in AI-Based Service Failures

Chapter 3. Now, Take your Hands from the Steering Wheel! How Trust, Well-Being and Privacy Concerns Influence Intention to Use Semi- and Fully Autonomous Cars

PART III
On the Ethics of AI

Chapter 4. Consumers' Perspectives on AI Ethics and Trust: an Explorative Investigation of Ethical Concerns Towards Autonomous Cars and Chatbots

Overall Theoretical, Methodological, Managerial Contributions, Research Limits and Future Research Directions

CHAPTER 3

NOW, TAKE YOUR HANDS FROM THE STEERING WHEEL!

HOW TRUST, WELL-BEING AND PRIVACY CONCERNS INFLUENCE INTENTION TO USE SEMI- AND FULLY AUTONOMOUS CARS

1. Introduction

In recent decades, a focus on the development of autonomous vehicles (AVs) has expanded due to their many potential benefits, such as increased safety, improved traffic efficiency and reduced emissions (Khastgir et al. 2018). On the one hand, manufacturers are rapidly progressing in their technological advancement of AV; on the other hand, the introduction of such a radically new technology is surrounded by a high degree of uncertainty (König and Neumayr 2017). Trust has long been recognized as critical to the adoption of automation, and it becomes even more important as the complexity of intelligent technological products increases (Shariff et al. 2017). A lack of experience with technology and a lack of transparency about automation's capabilities, limitations and underlying decision-making processes can make consumers distrust AVs or, in contrast, place too much trust in them due to consumers misunderstanding the real capabilities of AVs. Both ''overtrust" and ''undertrust" may be problematic. In fact, overly trusting a product might result in automation misuse, which could be dangerous in terms of safety (König and Neumayr 2017; Lee and See 2004). For instance, when driving semiautonomous level-2 cars, drivers might relax their traffic concentration, but assistance technology is not yet able to address complex traffic situations and accidents. However, not trusting a product enough may lead to automation disuse by foregoing improved performance potentials and benefits (König and Neumayr 2017; Lee and See 2004). In particular, by not using the functions of a level-2 assistance system, such as speed control or automated braking, consumers might risk accidents that could be avoided. In this regard, research suggests that by increasing road safety autonomous vehicles have the potential to increase consumers' well-being (Fagnant and Kockelman 2015; Hengstler et al. 2016; Shariff et al. 2017). Perceived quality of life can also be increased through less congestion, lower emissions and higher mobility for elderly and disabled persons (Fagnant and Kockelman 2015; Hengstler et al. 2016; Shariff et al. 2017).

However, although autonomous vehicles have the potential to increase well-being, privacy issues associated with sophisticated in-vehicle communication might decrease consumers' well-being (Du and Xie 2020).

Although research in the marketing domain has already started to investigate consumers' perceptions of fully autonomous cars in relation to trust, well-being, privacy concerns and usage intention (Bertrandias et al. 2021; Eggers and Eggers 2021; Hohenberger et al. 2017, 2017; Huang and Qian 2021), we still lack insights into how consumers' experiences with different levels of automation affect these perceptions (Rödel et al. 2014). In fact, as the technology is still evolving, researchers emphasize the need to adopt a more dynamic approach to comprehend how consumers' perceptions related to autonomous vehicles evolve across different development stages of the technology (Hengstler et al. 2016; König and Neumayr 2017). In regard to the market development of autonomous cars, exploring consumers' perceptions across different levels of automation is fundamental to research for three main reasons. First, an understanding of trust development and evolution across levels of automation is important to define the mechanisms that lead to trust calibration. Walker et al. (2018) define trust calibration as the alignment of drivers' subjective perceptions of safety and functionality with the actual reliability of their vehicle. To achieve trust calibration, drivers should first learn how the AV system works and behaves in a variety of situations, thus experiencing its different functions and becoming familiar with its different levels of automation (Walker et al. 2018). Second, in addition to automation's impact on trusting beliefs, the effect of AVs on consumers' well-being is a crucial topic of interest, which has received little attention despite transportation's effects on health and well-being having been widely recognized (Singleton et al. 2020). In this regard, elements, such as life satisfaction and positive emotions, can be significantly influenced by increased safety, travel satisfaction, and access to activities (Singleton et al. 2020). In fact, in addition to decreasing the risks of injuries and death from traffic collisions, autonomous vehicles might also improve travel experiences by removing the need to operate a vehicle, reducing many of the stresses associated with navigating urban traffic and congestion. Learning the functions across an AV's different levels of automation through increased experiences might also affect positive feelings due to a more relaxed and comfortable driving experience (Singleton et al. 2020). However, recent studies also highlight the need to investigate the important role of privacy risks in user evaluations of an autonomous system, which may actually decrease perceived subjective well-being (Bertrandias et al. 2021; Du and Xie 2020). In this regard, experiences with AV functions might be positively associated with the degree to which people are sensitive to risks (Cho et al. 2010). Third, when investigating new technologies, it is fundamental to comprehend the cognitive psychological mechanism that affects acceptance, in particular the utilitarian reasons beyond the usage of a technological product. In this regard, consumers' beliefs related to a technology, such as the perceived usefulness and perceived ease of use, have been proposed as major determinants of consumers' technical acceptance of autonomous vehicles (Choi and Ji 2015). As suggested by Venkatesh et al. (2003, 2011), increased experience with a system might affect consumers' cognitive evaluation of product functionalities and their intention to use them. For instance, when moving from level 2 to level 5, the increased complexity of a technology could potentially reduce consumers' usage intention. However, experience with the different functions might help consumers become familiar with them, decreasing their uncertainty regarding the complexity of a new technology (Venkatesh et al., 2011). On the other hand, at lower development levels (e.g., level 2), a lack of functionalities could negatively affect consumers' intention to use a technology compared to higher development levels with more reliable technical functions. Additionally, in this case, experiencing a technology can help adjust the expectations related to its performance (Venkatesh et al. 2011). However, despite the importance of consumers' experience with different functions and automation levels, most studies still neglect the key role of experience in affecting users' perceptions of a technology across different levels of automation (Huang and Qian 2021; Rödel et al. 2014). Thus, we address this research gap by investigating the following research question: how do consumers' trusting beliefs, well-being, privacy concerns and behavioral intentions to use fully autonomous cars differ and evolve after they experience different levels of automation?

To investigate this research question, we conducted four studies. Following Venkatesh and colleagues (Venkatesh et al. 2003, 2011), we integrated the UTAUT framework with the Trust Theory (Mcknight 2005; Mcknight et al. 2011), Privacy Calculus Theory (Dinev and Hart 2006) and Theory of Subjective Well-being (Diener 1999; Diener and Chan 2011). First, we conducted an online survey on full autonomous cars to test our model with a representative sample of the German population. Second, we replicated the results through a survey with a convenience sample in Germany. Third, by conducting a field study with a semiautonomous level-2 car, we implemented a within-subject design to investigate how consumers' perceptions of fully autonomous cars evolve before and after their driving experience with a semiautonomous level-2 car. At level 2 of automation, the driver must constantly supervise support features, such as adaptive cruise control and lane centering, and always be ready to steer, brake or accelerate. Thus, the driver is always driving, even when the support features are engaged (SAE International 2016). Fourth, we conducted a simulator study to investigate how consumers' perceptions of fully autonomous cars evolve while experiencing levels 2 through 5 of automation. At level 5, a car does not require the driver to take over (SAE International 2016).

The within-subject approach allows us to comprehend how consumers' perceived trust, privacy concerns, well-being and usage intentions regarding fully autonomous cars change and evolve across the development stages and levels of automation. In particular, by adopting a dynamic approach, this study addresses an emerging research gap by aiming to comprehend the way automation levels and experiences with different functions can increase customer acceptance (Huang and Qian 2021; Menon et al. 2020; Rödel et al. 2014).

2. Literature Review

2.1. Autonomous Cars and Levels of Automation

The concept of vehicle automation refers to the replacement of some or all of the human labor of driving with electronic and/or mechanical devices (Faisal et al. 2019; Shladover 2018). Autonomous vehicles (AVs) use artificial intelligence (AI) to control the driving task and require no or a minimum user input (Eggers and Eggers 2021). This disruptive innovation represents a highly attractive market for companies and an excellent opportunity for academic research (Eggers and Eggers 2021). Although research on autonomous driving is rapidly increasing (Bertrandias et al. 2021; Hohenberger et al. 2017; Huang and Qian 2021; Kaur and Rampersad 2018), most studies still neglect how different levels of automation affect users' perceptions of the technology (Rödel et al. 2014). In this regard, manufacturers have already started to equip new vehicles with sophisticated autonomous functions, which might help to reduce customer skepticism about autonomous vehicles and increase customer acceptance (Menon et al. 2020). In 2016, the Society of Automotive Engineers International (SAE International) presented a taxonomy with 5 levels of vehicle automation (SAE International 2016). This taxonomy has become an international standard in both manufacturing and academia (Faisal et al. 2019; Shladover 2018). According to this taxonomy, level 0 is defined as "no automation" because a car does not have any autonomous functions. In level 1, defined as "hands on", an AV system can control specific tasks, such as steering. Thus, the driver and the automated system share control of a vehicle during specific tasks. However, the driver is always in control. Level 2 is defined as "hands off". A level-2 vehicle can execute more tasks, such as accelerating, braking, and steering. A driver must monitor how the AV drives and be prepared to intervene immediately at any time. At level 3, defined as "eyes off", drivers can turn their attention away from driving tasks. When required, drivers must take back control. At level 4, defined as "mind off", self-driving is supported in limited spatial areas where a driver's attention is not required. Finally, at level 5, a steering wheel is optional, and no human intervention is required. In the present study, we adopt SAE International's (2016) definition of the levels of automation, focusing in particular on level 2 and level 5.

2.2. UTAUT Framework

When investigating technology, researchers often focus on the factors that drive acceptance and adoption. In this regard, technology acceptance and usage intentions have been studied through different theoretical lenses. Numerous studies focus on consumers' behavior related to information technology by applying the Theory of Reasoned Action (TRA) (Ajzen and Fishbein 1980) and its later revision, the Theory of Planned Behavior (TPB) (Ajzen 1985). Drawing on these, Davis (1989) proposes the Technology Acceptance Model (TAM) to shed light on the antecedents of behavioral intentions and attitudes toward technology usage, the perceived usefulness and ease of use of the technology in particular. The TAM has opened a path for a prolific stream of research on technology acceptance. In particular, Venkatesh et al. (2003) extend and update the traditional model, proposing the Unified Theory of Acceptance and Use of Technology (UTAUT), which provides a refined view of how the determinants of intention and usage of a technology evolve over time. In this regard, the authors introduce new constructs, such as performance expectancy, effort expectancy, social influences and facilitating conditions, and investigate the moderating roles of age, gender, experience, and voluntariness to predict consumers' behavioral intention to use a technology (Venkatesh et al. 2016). The UTAUT has been applied to the study of a variety of technologies in both organizational and nonorganizational settings and has often been integrated with other theories and additional constructs (Venkatesh et al. 2016). In the present study, we apply the UTAUT model to the context of autonomous cars, as it is more parsimonious and recent than rather traditional models, such as the TAM (Davis 1989; Meyer-Waarden and Cloarec 2021; Venkatesh et al. 2003, 2011, 2012).

In addition, as Venkatesh et al. (2011) suggest, the generalizability of the beliefs defined by the UTAUT has been demonstrated by a number of studies on the adoption of different technologies (e.g., Oliveira et al. 2014; Wang and Yang 2005). We focus on the utilitarian components of the UTAUT, effort expectancy and performance expectancy in particular; these play fundamental roles in investigations of the cognitive antecedents of behavioral intentions (Venkatesh et al. 2011). Performance expectancy is defined as the degree to which an individual believes that using a system will facilitate gains in one's job performance (Venkatesh et al. 2003). This concept reflects the construct of perceived usefulness proposed by Davis (1989). In the context of autonomous cars, performance expectancy refers to the belief that using autonomous functions improves the execution of driving tasks and driving performance. On the other hand, effort expectancy, which is conceptually contiguous with Davis's (1989) construct of ease of use, refers to the degree of ease associated with the use of a system (Venkatesh et al. 2003). In the context of autonomous cars, effort expectancy is related to the degree to which a user perceives autonomous functions to be easy to use.

According to the UTAUT, performance expectancy and effort expectancy influence behavioral intentions toward a technology, which determine technological use (Venkatesh et al. 2016). Research suggests that the more complex an innovation is, the lower consumers' intentions to use it (Oliveira et al. 2014). At first, consumers might perceive semiautonomous functions to be difficult to use. However, consumers' perceptions about effort expectancy tend to change after experiencing a technological product (Oliveira et al. 2014). Therefore, as their experiences and familiarity with autonomous functions increase, consumers might perceive them to be easier to use (Hartwich et al. 2018; Venkatesh et al. 2011). Consumers are more satisfied with the performance of a technology when its facility of usage is higher (Meuter et al. 2005). Thus, effort expectancy should help to increase the expectancy related to the driving performance of the car. Moreover, a behavioral intention—in particular the intention to use an autonomous vehicle—is positively affected by performance expectancy (Venkatesh 2003, 2011). In fact, the more users believe that a fully autonomous car properly performs, the keener they will be to adopt it (Choi and Ji 2015; Meyer-Waarden and Cloarec 2021). Thus, we propose:

H1: The effort expectancy of driving a fully autonomous car has a positive effect on its performance expectancy.

H2: The performance expectancy of driving a fully autonomous car has a positive effect on the behavioral intention to use.

2.3. Well-Being

One of the main promises of autonomous vehicles is to promote consumer well-being, thereby improving quality of life and life satisfaction (Peters et al. 2018). On the one hand, the amount of attention from marketing research to the concept of psychological well-being has increased (Munzel et al. 2018; Papa et al. 2020), but few studies have investigated it in relation to intelligent technologies and, in particular, to autonomous driving (Bertrandias et al. 2021; Schuster et al. 2013). However, fully autonomous vehicles might have the potential to increase consumers' subjective well-being, improving their perceived quality of life due to higher traffic efficiencies, lower emissions, less stress from driving and improved accessibility to mobility for older and disabled individuals (Bertrandias et al. 2021; Faisal et al. 2019). For this reason, we enhance the UTAUT model with the construct of subjective well-being (Diener et al. 1999; Diener and Chan 2011). Psychological research has investigated well-being and has mainly distinguished two different types: eudaimonic well-being and hedonic well-being (Ryan and Deci 2001). Eudaimonic well-being is achieved through developing one's best attributes, based on one's deeper principles, by acting to the best of one's ability and developing one's potential (Huta and Ryan 2010). Hedonic well-being is achieved through one's pursuit of pleasure, enjoyment, and comfort; in other words, it concerns the experiences of pleasure versus displeasure. There may be many ways to evaluate the pleasure/pain continuum in human experience, but most research within the new hedonic psychology field has used the assessment of subjective well-being (SWB) (Diener 1984; Diener et al. 1989; Diener and Chan 2011). One's SWB consists of three components: life satisfaction, the presence of a positive mood, and the absence of a negative mood, which are collectively summarized as happiness (Diener 1984; Diener et al. 1989; Diener and Chan 2011). Moreover, Sirgy et al. (2012) conceptualize subjective well-being as one's personal judgments of happiness and life satisfaction. In the context of autonomous driving, Bertrandias et al. (2021) adapt Diener et al.'s (1999) definition of subjective well-being, defining it as consumers' "perceived ability of autonomous products to enhance positive emotions and life satisfaction" (Berdrandias et al. 2021, p. 4). Accordingly, in the present study, we investigate the subjective well-being consumers experience when driving autonomous cars, particularly in relation to their increased quality of life and positive feelings (Diener et al. 1999; Sirgy et al. 2012).

Research shows that technological products can positively affect consumers' well-being, improving their quality of life by assisting them in daily life activities (Lu et al. 2019; Riva et al. 2012). In this regard, the "Positive Technology" paradigm suggests that the use of technology can improve the quality of individuals' personal experiences through structuring, augmentation, and/or replacement (Calvo and Peters 2014; Riva et al. 2012). The relationship between well-being and technological usage has been studied in different contexts. For instance, in the context of mobile banking, Rahman et al. (2017, 2020) suggest that the ease of use and usefulness of a technology can positively affect one's subjective well-being (Rahman et al. 2017, 2020). In the context of hedonic consumption, Zhong and Mitchell (2012) argue that one's subjective well-being can be increased by the benefits associated with a technological product. Users can also increase their subjective well-being by using social media sites (Munzel et al. 2018) and playing video games (Kim and Hall 2019). Additionally, in the context of self-driving cars, researchers have recently started to investigate well-being by considering the potential benefits that the technology can bring (André et al. 2018; Bertrandias et al. 2021; Meyer-Waarden and Cloarec 2021). In this regard, André et al. (2018) suggest that autonomous cars might contribute to consumers' well-being, assisting their decision-making process by making it easier and more efficient. Thus, the utilitarian value of a technology, particularly its ability to assist and facilitate driving tasks, can increase consumers' perceived quality of life and feeling of well-being. Accordingly, Ettema et al. (2011) suggest that travel conditions improved through, for instance, an implementation of easy-to-use functions, could increase consumers' subjective well-being by offering them a more pleasant experience of travel and improving their access to other activities. Thus, the easier functions are to use and the better they facilitate driving tasks; the more consumers' well-being may be increased through a more pleasant driving experience. Accordingly, Bertrandias et al. (2021) suggest that due to the support functions of AVs systems, individuals can access a more relaxed driving experience. In addition, autonomous cars may increase drivers' well-being due to their perceived usefulness and performance expectancy. In this regard, a high degree of satisfaction with a technology due to its successful performance enhances users' perceived quality of life and needs fulfilment (Lu et al. 2021; Martínez-Caro et al. 2018). Thus, we propose:

H3a: Effort expectancy has a positive effect on well-being.

H3b: Performance expectancy has a positive effect on well-being.

In addition, the happier and more satisfied individuals are with a technological product, the more likely they are to adopt and use it (Lu et al. 2021). In this regard, the literature shows that increased well-being can play an important role in fostering consumers' technological adoption and usage (Munzel et al. 2018). According to transformative consumer research, subjective well-being increases positive experiences, which ultimately and positively affect behavioral intentions, such as usage and adoption (Anderson et al. 2013; Davis and Pechmann 2013). In fact, when consumers improve their subjective well-being with a certain activity, they may want to continue undertaking that activity, which makes them feel content and satisfied (Kim and Hall 2019; Meyer-Waarden and Cloarec 2021). The more consumers perceive that a technology increases their quality of life, the more predisposed they are to use it. Thus:

H4: Well-being has a positive effect on the behavioral intention to use a fully autonomous car.

2.4. Trust in Technology

The importance of trust in different domains, especially in the adoption and usage of new technologies, has been demonstrated (Gefen et al. 2003). According to McKnight et al. (2011), the integration of trusting beliefs into technology acceptance models is fundamental, as trusting beliefs entail an experiential trust component that is not often captured (McKnight et al. 2011). Trust, a psychological concept originally applied to interpersonal relationships, is defined as the individual attitude that an agent will help achieve one's goals in a situation characterized by uncertainty and vulnerability (Lee and See 2004). In the behavioral literature, most researchers adopt Mayer, Davis and Schoorman's (1995) three dimensions of interpersonal trust—ability, benevolence, and integrity. Similar to interpersonal trust, trust in technology reflects one's beliefs about a technology's ability to deliver on the promise of its objective characteristics (McKnight 2011). Trust in technology is fundamental, as people tend to use and rely on autonomous technologies they trust and to reject autonomous technologies they do not trust (Lee and See 2004). In fact, trust is commonly used to reduce uncertainty or vulnerability in exchanges, especially when individuals have limited knowledge or prior experiences with a technology (Oliveira et al. 2014). As autonomous technologies become more complex, investigating trust becomes increasingly important to prevent situations in which consumers *misuse or disuse* a technology, compromising their safety. *Misuse* refers to an overreliance on automation resulting from too much trust; in other words, the individual overtrusts a machine because his or her trust exceeds the system's capabilities (Parasuraman and Riley 1997). In the case of autonomous vehicles, a misuse of automation could result in dangerous situations when a driver relies on a car to drive autonomously but the AV is not capable of navigating the current driving situation. *Disuse* refers to the underutilization and distrust of automation due to an individual's rejection of the capabilities of automation (Parasuraman and Riley 1997). Thus, in the specific case of autonomous vehicles, a driver would not use the automated driving functions of an AV in situations that the car could navigate, thus losing the potential safety and comfort benefits that characterize driverless cars.

One of the first taxonomies of trust in automation was proposed by Muir (1994), who discussed trust in terms of predictability, dependability, and faith. Additionally, Lee and Moray (1992) identified three factors that influence trust: 1) Performance is linked to the ability to achieve a user's goals of reliability and predictability. In this case, the attribution of trust can be derived from one's direct observation of system behavior. 2) Process is the extent that automation's algorithms are appropriate for a situation and understandable. Here, trust is the result of one's understanding of the underlying mechanism of automation. 3) Purpose refers to the degree to which automation is being used according to its designer's intent. Lee and See (2004) updated the taxonomy proposed by Lee and Moray (1992), highlighting the elements associated with performance (e.g., competence, ability, reliability), process (e.g., persistence, integrity, predictability, dependability), and purpose (e.g., loyalty, benevolence, faith). In addition, McKnight (2011) investigated the characteristics or attributes of a trustee, suggesting that trust in a specific technology is reflected by three trusting beliefs: functionality, helpfulness and reliability. Users' assessments of attributes reflect their beliefs about a technology's ability to deliver on the promise of its objective characteristics (Mcknight et al. 2011). Functionality is defined as the capacity of a technological product to complete a required task. According to McKnight (2011), the functionality of a technology is conceptually similar to the competence of a person because both represent users' expectations about a trustee's capability. In the context of an autonomous car, consumers assess whether AV technology delivers the functionalities promised to properly complete the driving task. Helpfulness refers to a feature of the technology itself. In particular, helpfulness refers to users' beliefs that a technology provides adequate, effective, and responsive assistance through the implementation of a help function (Mcknight 2005; Mcknight et al. 2011). Helpfulness mirrors the concept of benevolence in interpersonal trust (Mcknight et al. 2011). In fact, when interacting with a person, individuals evaluate whether the other party cares enough to offer help when needed. When interacting with a technology, although the user is aware that the machine lacks caring emotions, as it does not have moral agency and intentionality, he or she still evaluates whether the technology has a help function capable of providing advice that is useful for completing the driving task (Mcknight 2005; Mcknight et al. 2011). Reliability refers to a user's expectation that a technology works consistently and predictably. It is conceptually contiguous with the interpersonal trust concept of integrity. Although a technology lacks purposeful intentions and volition, it might still demonstrate flaws or situational events that cause failures, thereby failing to function consistently and predictably (Mcknight et al. 2011). According to Mcknight et al. (2011), "the three trusting beliefs of functionality, helpfulness and reliability reflect the essence of trust in a specific technology, representing the knowledge that users have cultivated by interacting with the product in different contexts, gathering data on its available features, and noticing how it responds to different actions" (Mcknight et al. 2011, p. 9).

By focusing on the technology itself, researchers can evaluate how trusting beliefs regarding the specific attributes of a technology, particularly its functionality, helpfulness and reliability, relate to consumers' usage behaviors (Mcknight et al. 2011). In this regard, trust is known to be a major determinant of one's acceptance of automation (Choi and Ji 2015; Gefen et al. 2003; Lee and See 2004). When properly operating, a technology can shape users' perceptions of consistency and reliability, positively affecting their usage intentions (Choi and Ji 2015). According to Mcknight et al. (2011), the more users believe a technological product has a higher level of functionality, thus having the necessary capabilities to correctly perform the tasks it is programmed to do, the more willing they will be to use the technological product. In this regard, in the case of autonomous cars, a user's expectation of the system's functionality, particularly related to the successful and proper performance of driving tasks, determines trust, which is fundamental for acceptance (Choi and Ji 2015). Additionally, responsive aid, and thus the helpfulness of autonomous functions, has been shown to determine consumers' trust in automation and increase their behavioral intentions of usage (Choi and Ji 2015; Mcknight et al. 2011). In addition to the functionality and the helpfulness of functions, a user's perception of the accuracy of autonomous technologies and of the possibility to predict and understand the operation of autonomous vehicles can play a fundamental role that affects one's behavioral intention to use a technology (Choi and Ji 2015). Moreover, as Mcknight et al. (2011) suggest, the trusting beliefs of functionality, helpfulness, and reliability, which collectively constitute one's knowledge-based trust, are defined and adjusted through one's experiences with a specific technology over time. In this regard, knowledge-based trust, or experiential trust, means that the trustor knows a technology well enough to predict its functionality, helpfulness and reliability in different situations (McKnight et al. 2011). Developing consumers' knowledge-based trust, which in the particular case of AV technology is based on their trusting beliefs of functionality, helpfulness and reliability, may foster technological usage (McKnight et al. 2011). Thus, we propose:

H5a: The functionality of a fully autonomous car has a positive effect on the behavioral intention to use.

H5b: The helpfulness of a fully autonomous car has a positive effect on the behavioral intention to use.

H5c: The reliability of a fully autonomous car has a positive effect on the behavioral intention to use.

2.5. Trusting Beliefs and Well-Being

The link between trust and well-being has been widely investigated by the social sciences (Helliwell and Huang 2011; Michalos 1990; Poulin and Haase 2015). In the context of interpersonal relationships, research shows that a lack of interpersonal trust can significantly decrease an individual's quality of life and perceived well-being, inducing stress and anxiety (Poulin and Haase 2015; Sirgy et al. 2012). When trusting another person, individuals tend to evaluate the trustee's benevolence, particularly assessing the trustee's intentions to benefit the trustor, thereby improving his or her well-being (Mayer et al. 1995). If the evaluation is negative, individuals' quality of life, sense of happiness and well-being might be undermined (Poulin and Haase 2015; Sirgy et al. 2012). In fact, a lack of trust may cause distress and negative emotions, decreasing one's psychological safety (Kramer and Cook 2004). Thus, fostering trusting beliefs about other parties is fundamental to improve individuals' well-being and positive feelings, decreasing their perceptions of uncertainty and vulnerability. Additionally, when using and interacting with a technology, individuals form trusting beliefs, particularly evaluating whether the technology properly performs (functionality), provides adequate and responsive help for users (helpfulness) and is predictable over time (reliability) (McKnight et al. 2011). Similar to interpersonal relationships, when users interact with a technological product, their trusting beliefs tend to affect their assessments of the product's ability to improve or decrease their well-being. In the context of autonomous vehicles, the more the technology is perceived to be trustworthy, the more individuals experience the safety and relaxation needed to enjoy the driving experience. Thus, we suggest that users' trusting beliefs of functionality, helpfulness and reliability might increase their subjective well-being, offering them a more pleasant driving experience by assisting individuals in driving tasks and decreasing the feelings of uncertainty and vulnerability related to the technology.

H6a: The functionality of a fully autonomous car has a positive effect on well-being.

H6b: The helpfulness of a fully autonomous car has a positive effect on well-being.

H6c: The reliability of a fully autonomous car has a positive effect on well-being.

2.6. Privacy Concerns

When discussing the acceptance of a new technology, privacy concerns are often highlighted as one of the most relevant issues that hinder consumers' adoption of new technological products (Gozman and Willcocks 2019; Malhotra et al. 2004; Smith et al. 1996; Wirtz and Lwin 2009). In this regard, the privacy concerns related to technology usage have been widely investigated in the marketing and information system literature (Malhotra et al. 2004; Martin and Murphy 2017; Thomaz et al. 2020; Wirtz and Lwin 2009). Privacy concerns refer to consumers' beliefs, attitudes, and perceptions about their privacy (Malhotra et al. 2004; Martin and Murphy2017; Smith et al. 1996). Privacy is defined as the appropriate flow of and control over personal information within distinctive social contexts (Martin and Murphy 2017; Nissenbaum 2010). Consumers are increasingly concerned about privacy issues due to the pervasiveness of technology, which can be perceived as intrusive, despite its potential benefits, such as increased personalization (Cloarec 2020). In this regard, the privacy issues related to technological usage are mainly related to control over the dissemination and use of consumer information, for example, a user's demographic data, search history, or personal profile information (Martin and Murphy 2017). In the context of autonomous cars, consumers' privacy concerns relate to AVs sharing their location, facial, and travel-pattern data (Bonnefon et al. 2016; Gurumurthy and Kockelman 2020). AVs have the ability to autonomously select routes and define travel plans, thus compromising privacy in terms of the paths they choose (Kaur and Rampersad 2018). In addition, vehicle-to-vehicle technology, by means of which autonomous vehicles are able to dynamically exchange information to improve traffic efficiency, can compromise users' privacy by controlling communication with other cars (Kaur and Rampersad 2018). Privacy concerns can directly affect consumers' intentions and adoption behaviors (Angst and Agarwal 2009). In fact, they can diminish consumers' usage intentions of new technologies by fostering their uncertainty and lack of control over their personal information (Luo 2002; Thomaz et al. 2020). According to Culnan and Bies (2003), individuals are more concerned about disclosing personal information when they perceive that the overall benefits of such disclosure are lower than the assessed risk of this disclosure. This cost-benefit analysis is defined as the privacy calculus (Dinev and Hart 2006; Stone and Stone 1990). According to Dinev and Hart (2006), individuals are more likely to use a new technology when the levels of trust and positive beliefs related to the technology are higher than individuals' levels of privacy concerns. However, higher levels of beliefs related to privacy risks also increase users' resistance to personal information disclosure and technological usage (Dinev and Hart 2006). For instance, in the context of autonomous cars, Wang and Zhao (2019) suggest that consumers' concerns related to privacy can reduce their behavioral intention to use the technology. Thus, we propose:

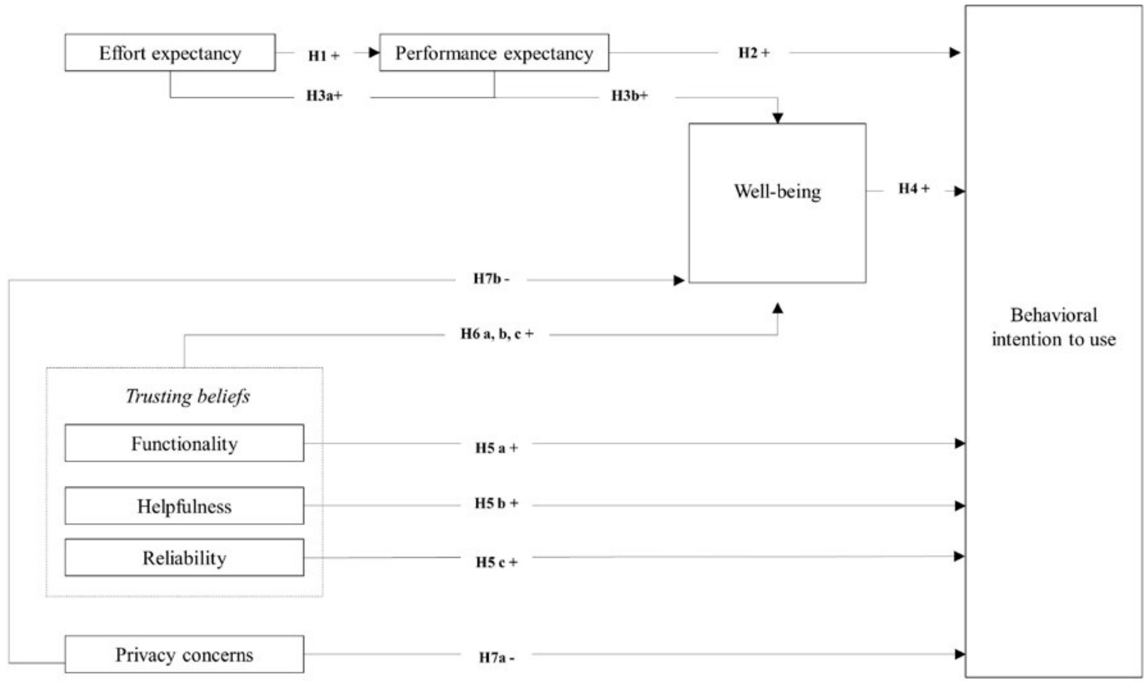
H7a: Privacy concerns about fully autonomous cars have a negative effect on the behavioral intention to use.

Privacy concerns have also been investigated by the transformative consumer research field in relation to well-being (Anderson et al. 2013). In this regard, Anderson and colleagues (2013) suggest that through the introduction of new technological products, which are often endowed with sensors and cameras and able to access consumers' geo-location and other sensitive data, consumers might be exposed to risks related to privacy, which could negatively affect their well-being. In fact, while increased information flow increases consumers' well-being through more accurate targeting, consumers can feel a lack of control over their personal information, which might engender negative feelings (Petty 2000). In this regard, many researchers have highlighted the need to further investigate how privacy risks related to complex intelligent technologies, such as driverless cars, might compromise consumers' well-being (André et al. 2018; Du and Xie 2020; Munzel et al. 2018). Du and Xie (2020) suggest that the higher the level of intelligence and interactivity of a technological product is, the more consumers can be exposed to privacy risks. In particular, the authors argue that through the proliferation of interconnected smart devices, many AI-enabled products interact continuously with consumers to gather data and improve performance, making consumers more likely to confront challenges related to privacy and their well-being. Thus, we propose:

H7b: Privacy concerns about fully autonomous cars have a negative effect on well-being.

The hypotheses are formalized in the conceptual model that is shown in Figure 18.

Figure 18 Conceptual model

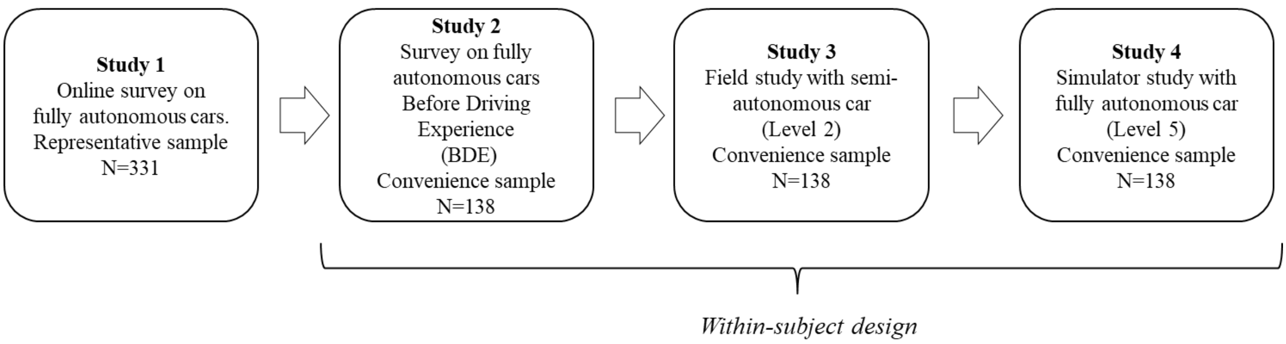


3. Methodology

3.1. Research Design

We conducted a total of four studies (Figure 19). First, we conducted an online survey to test our conceptual model with a representative sample of the German population from a professional panel company (N=331) (Study 1). Second, we replicated the results of Study 1 with a German convenience sample (N=138) to investigate consumers' perceptions of fully autonomous cars before their driving experience (Study 2, Before Driving Experience). Third, to investigate how consumers’ trust, well-being and behavioral intentions evolve across different levels of automation, we conducted a field study with the same participants as Study 2 (N=138) to investigate consumers’ perception toward fully autonomous cars after experiencing level-2 automation (Study 3, level 2). In particular, after we investigated users’ perceptions of fully autonomous cars before their driving experience (Study 2), the same respondents as Study 2 were invited to drive a level-2 semiautonomous car (within-subject design). After their driving experience with level-2 automation, participants completed a questionnaire concerning their perceptions of fully autonomous cars. After one week, we conducted a simulator study with a fully autonomous level-5 car with the same respondents as Studies 2 and 3 (N=138) (Study 4, level 5). After their driving experience with level-5 automation, participants once again completed the questionnaire concerning their perceptions of fully autonomous cars. Each study is described in detail in the next paragraphs.

Figure 19 Research design



3.2. Study 1

To test and validate our conceptual model, we first conducted an online survey to investigate consumers’ perceptions of fully autonomous cars at level 5. The data were collected from 02/06/2020 to 17/06/2020 through a professional panel provider. We recruited participants according to two main selection criteria: currently a resident in Germany and fluent in German. We selected only participants possessing a European driving license category B, which permits the operation of vehicles up to 3500 kg with up to eight passenger seats. To obtain a representative sample of the German population, we implemented quotas according to the gender and age distribution of the Federal German Statistical Office, which was updated in 2018. In total, 884 participants were excluded after the quotas were full. Drawing from Meade and Craig (2012), we included an attention check to ensure the quality of the data ("Please, select disagreement for this item"). After removing participants who did not meet the initial criteria of possessing a driving license B, who exceeded the quota, or did not pass the attention check, the dataset comprised 369 observations. In addition to using the above measures to reject the participants who did not meet the criteria, we checked for respondents' misconduct by assessing their time responses and variance (Collier 2020). We obtained a final sample of 331 responses (Table 35).

Table 35 Sample description of Study 1

		Gender		**Total**
		Women	**Men**	
Age	18 - 29	27	25	52
	30 - 39	27	27	54
	40 - 49	29	26	55
	50 - 59	36	29	65
	60 - 69	22	23	45
	>70	30	30	60
Total		**171**	**160**	**331**

3.3. Study 2

We conducted a second replication study to investigate consumers' perceptions of fully autonomous cars before their driving experience (BDE). The data were collected from 01/07/2020 to 01/08/2020. We recruited a convenience sample of 139 German participants through an advertising campaign at the Baden-Württemberg Cooperative State University (DHBW). We only selected participants possessing a driving license B. One participant was not able to continue the study and was removed from the study. Thus, the final sample included 138 participants (Table 36).

Table 36 Sample description of study 2

		Gender		Total
		Women	**Men**	
Age	18-29	14	35	49
	30-39	9	11	20
	40-49	9	10	19
	50-59	16	16	32
	60-69	3	7	10
	>70	0	8	8
Total		**51**	**87**	**138**

3.4. Study 3

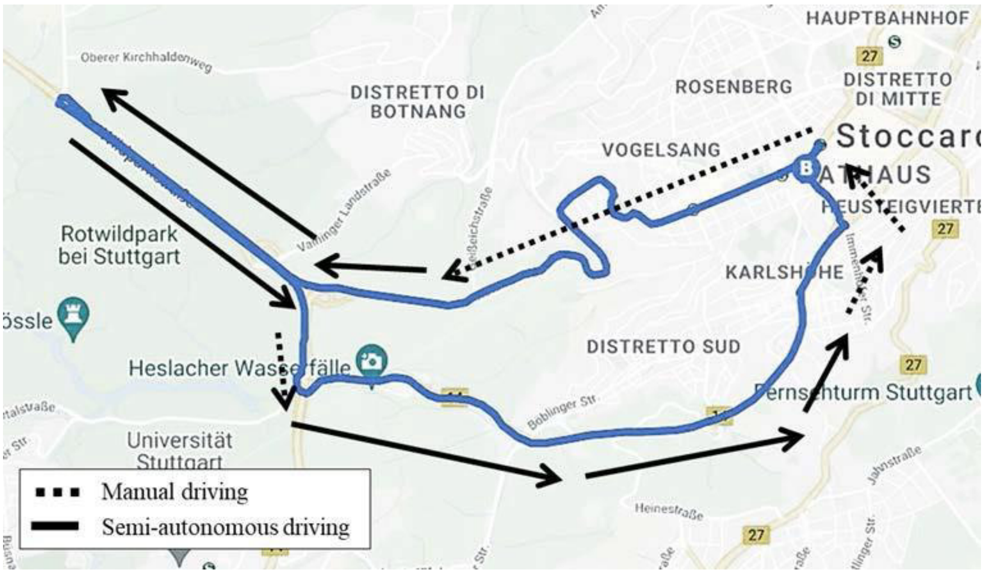
Next, we conducted a third study to investigate consumers' perceptions of fully autonomous cars after they had driven a semiautonomous level-2 car in a real driving environment through a field study in the Stuttgart area[1] (Level 2). The participants were the same as Study 2 and were evaluated through a within-subject design (Table 36). We used an electric Mercedes-Benz EQC (Figure 20) with level-2 automation and the following semiautonomous functions: automatic lane keeping, automatic lane changing, automatic distance keeping, automatic speed control, and automated braking. Drawing from Kuhn and Marquardt (2019), we used a standardized test track in Stuttgart, Germany (Figure 21). That is, Kuhn and Marquardt (2019) identify two main application domains for automated driving: highway driving and urban driving. Urban and highway driving have been extensively tested in transportation research (Beggiato et al. 2015; Beggiato and Krems 2013; Hartwich et al.

[1] Stuttgart is the capital and largest city of the German state of Baden-Württemberg. Its area has a population of 635,911, making it the sixth largest city in Germany. 2.8 million people live in the city's administrative region and 5.3 million people in its metropolitan area, making it the fourth largest metropolitan area in Germany.

2018). Urban scenarios present special challenges due to their complexity and dynamic behavior. Traffic is dense, several types of road users or static obstacles are present, and the driving task includes negotiating traffic at roundabouts, intersections and merging maneuvers. These particular conditions facilitate the testing of specific AV functions, such as automated braking, feedback on the gas pedal and steering wheel, automated cruise control and fully supervised automated control. Concerning an autonomous vehicle on a highway, this context facilitates accounting for additional functions, particularly entering and exiting highways, performing lane changes or filter-in maneuvers and navigating dangerous areas, such as the end of a traffic jam. In the urban condition, speed limits were fixed according to German legislation (40 km per hour). In the highway condition, speed limits were fixed to the speed limit of 80 km/h. Before starting the field experiment, each participant received a general introduction to the automated driving system. The test drivers were also informed that they were responsible for the entire driving process and had to respect traffic regulations. At the start of the test driving, participants were asked to manually drive the vehicle to familiarize themselves with it. After the familiarization phase in the urban scenario, they were asked to initially activate the semiautonomous functions in the highway scenario before they did so in the urban scenario. The driving experiences lasted an average of 36 minutes. After their driving experience, participants completed a postquestionnaire.

Figure 20 Mercedez-Benz EQC

Figure 21 Standardized test track



3.5. Study 4

One week after their driving experience with level-2 automation, the same participants as Study 2 and Study 3 were invited to return to test fully autonomous cars in a simulated environment (Level 5). The period of time between the two experiments ensured the independence of participants' multiple exposures, which is a fundamental condition in "within-subject" design experiments that investigate how individual behavior changes when the circumstances of an experiment change (Charness et al. 2012). Thus, we conducted a simulation study within a simulated environment representing an autonomous level-5 car to test the full AV functionalities.

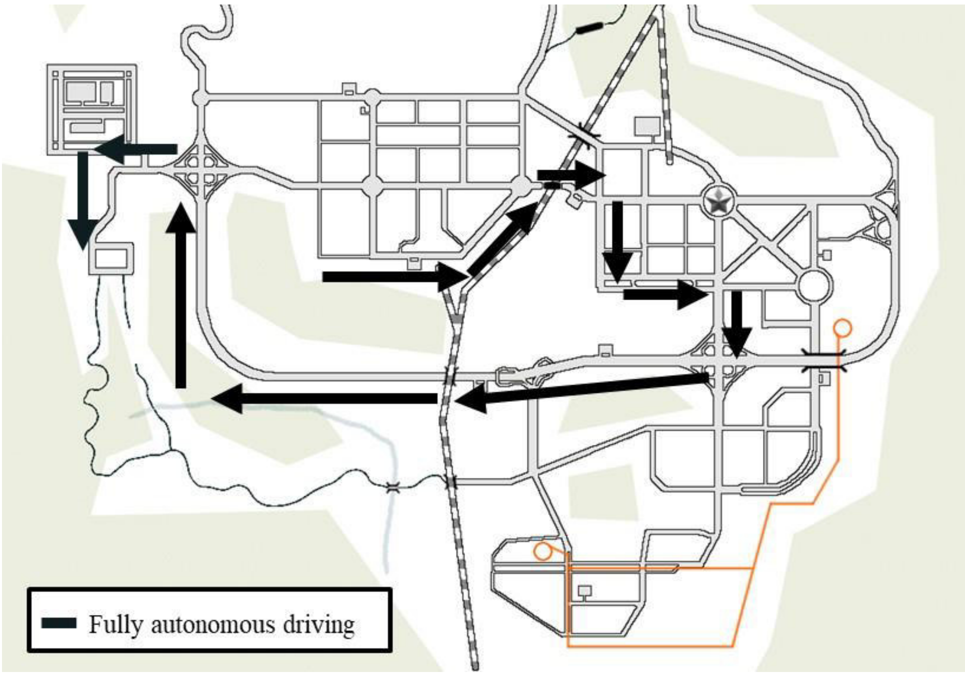
3.5.1. The Driving Simulator

The simulator was developed by an engineer from DHBW (Figure 22; Figure 23). The simulator was composed of three curved screens that extended participants' peripheral vision, a real car seat and a cabin that simulated the car's interior. We did not include a steering wheel or gas pedal, based on the potential characteristics of fully autonomous level-5 cars (SAE International 2016). To design the scenarios of the simulators, we used City Car Driving – a realistic, immersive driving simulator with an environment that is as realistic as possible. Driving simulators are generally used for testing and improving drivers' urban driving skills and are able to support training (Dosovitskiy et al. 2017). The simulator commands allowed us to test different functionalities, which included steering, accelerating, decelerating, lane changing and braking. The environmental properties of the simulator included weather conditions, illumination, and density of cars and pedestrians. To consistently test the effect of the increased automation on the fully autonomous driving experience and to ensure comparability between the two experiments, we replicated the same weather conditions – no rain and daily light – and driving contexts used in the field experiment (Study 3), highway scenario and urban scenario (Figure 24).

Figure 22 Driving simulator (a)

Figure 23 Driving simulator (b)

Figure 24 Test track simulator



We manipulated traffic conditions to increase realism and to test drivers' responses (Khastgir et al. 2018). In this regard, Paxion et al. (2013) summarize the taxonomy of situation complexity as dependent on road design (i.e., motorways vs. rural roads vs. urban roads), road layout (straight vs. curved, level vs. inclined, junction vs. no junction) and traffic flow (high density vs. low density). Accordingly, the urban scenario was designed to invoke the sensation of driving in the downtown core of a populated city center; thus, it involved more intersections, turns, pedestrians and cut-in situations than the highway scenario. The highway scenario, by comparison, involved fewer of these elements. Concerning pedestrians, virtual pedestrians in a simulator with a 180◦ projection system provide a more realistic yet safe test environment (Chrysler et al. 2015). Thus, our scenarios included pedestrian dummies for them to appear as natural and plausible as possible. Following Chrysler et al. (2015), we decided to keep the path and speed of the pedestrians constant to simplify the experimental design.

In addition, drawing from Chrysler et al. (2015), the number of events per drive in the urban scenario was set at one every 3 minutes. The driving speed of their study (30 mph, which is equal to 48 km/h in the urban section) and their pilot testing demonstrates that this event spacing is sufficient to integrate periods of uneventful driving. In addition to pedestrians, to increase realism, we used cars that cut in line. In fact, cut-in scenarios are very common in traffic and have potential collision risks (Ma et al. 2019). Cut-in behavior is one reason why advanced technologies akin to autonomous vehicles need to be tested in various complicated situations before going into mass production (Bazilinskyy et al. 2018; Bazilinskyy and de Winter 2015). To summarize, we incorporated four critical events. 1) A car cuts in line, and the autonomous car stops for safety reasons. Warning lights flash. 2) A car in front drives in a zigzag pattern for 4 seconds, and the autonomous car stops for safety reasons. 3) A pedestrian runs into the street and crosses it. The autonomous car stops, and warning lights flash. 4) A car ahead makes an emergency stop on the highway, and the autonomous car switches lanes while warning lights flash upon entering the other lane.

To ensure that the simulator was perceived as realistic, we measured the realism of the simulator on a 7-point Likert scale, adapting the scale of Al-Shihabi and Mourant (2003) (I felt like I was driving a real car; The responses of other vehicles in the simulation felt realistic; The accelerations and decelerations in the simulator felt realistic; The steering in the simulation felt realistic). On average, the simulator was perceived as very realistic (M=4.33, SD=1.21).

3.5.2 Procedure of the Simulator Study

We first introduced the simulator to participants. The driving simulation involved a familiarization phase of 2 minutes, and the actual simulation lasted 12 minutes. Training sessions are common in human-technology interaction studies to prevent learning effects and to familiarize participants with a new system. Such training is also commonly a part of driving simulator experiments. The main reasons for training include becoming familiar with interior components, such as indicators and switches, learning to interact with study-specific factors and reducing simulator sickness (Hock et al. 2018). Nevertheless, there is no uniform procedure for simulator training (e.g., time, distance, driving tasks) (Hock et al. 2018). For instance, sessions for training can last 5 minutes (Thiffault and Bergeron 2003), 10 minutes (Dorn and Barker 2005) or 30 minutes (van Winsum et al. 1999). In any case, most driving simulator studies have practice sessions lasting 5–15 minutes (McGehee et al. 2001). In this regard, Chrysler et al. (2015) argue that a warm-up drive from 5 to 10 minutes with no events or hard stops and minimal turns allows drivers to become accustomed to vehicle handling and visual environments and gives researchers an opportunity to observe any symptoms of simulator sickness. Nevertheless, although spending more time in the simulator can improve adoption, the probability of simulator sickness may increase (Hock et al. 2018). Thus, to allow participants to familiarize themselves with the simulator and prevent simulator sickness, we limited the training and adaptation warm-up drives to 2 minutes. In addition, to ensure that any potential simulator sickness symptoms did not affect the study, we measured sickness on a seven-point Likert scale simulator, adapting the scale of Kennedy et al. (1993) (During the simulation, I felt general discomfort; fatigue; headache; eyestrain; difficulty focusing; increased salivation; sweating; nausea; difficulty concentrating; fullness of head; blurred vision; dizziness; vertigo; stomach awareness; burping). Only one participant was not able to continue the experiment because of simulator sickness. Overall, the rest of the participants did not experience simulator sickness during the experiment (M=2.02; SD=.96). After their simulated driving experience, participants completed a postevaluation questionnaire.

3.6. Measurement Scales

All measurement scales were based on and adapted from previous studies. We used the same scales across the four studies (Table 37). Responses were collected based on a seven-point Likert scale. We measured effort expectancy and performance expectancy by using the scales of Davis (1989) and Venkatesh et al. (2012). We used the scale of Malhotra et al. (2004) to measure privacy concerns. Trusting beliefs of helpfulness, functionality and reliability were measured by using the scale of Mcknight et al. (2011). We adapted the subjective well-being scale of Diener (1984) and of Diener and Chan (2011). Behavioral intention to use was adapted from Kulviwat et al. (2007). We conducted a confirmatory factor analysis by using the R 3.6.1 software and the lavaan package (Rosseel 2012). The scales showed satisfactory psychometric properties for reliability (a >.07), convergent validity (> 0.5) (Table 37), and discriminant validity in Study 1 (Table 38), in Study 2 (Table 39) in Study 3 (Table 40) and in Study 4 (Table 41) (HTMT < .85; Henseler et al. 2015). The measurement models achieved a good fit, according to the usual fit indices, for all four studies: RMSEA < 0.08, CFI > 0.90 and TLI > 0.90 (Table 42).

Table 37 Reliability and convergent validity of the scales

	Study 1 Survey N=331	**Study 2 Before Driving Experience N=138**	**Study 3 Level 2 N=138**	**Study 4 Level 5 N=138**	**Source**
Effort Expectancy	α = .93 AVE = .77	α = .88 AVE = .65	α = .88 AVE = .65	α = .83 AVE = .54	Davis (1989) and Venkatesh (2012)
Driving autonomous cars would be easy for me.	.84	.81	.84	.75	
I would find it easy to get autonomous cars to do what I want it to do.	.86	.72	.71	.64	
My interaction with autonomous cars would	.88	.81	.84	.73	

be clear and understandable.					
I would find autonomous cars easy to use.	.93	.92	.88	.90	
Performance Expectancy	α =.94 AVE =.85	α =.81 AVE =.57	α =.85 AVE =.70	α =.90 AVE =.76	Davis (1989) and Venkatesh (2012)
Autonomous cars would enable me to accomplish tasks more quickly.	.88	.60	.78	.84	
Using autonomous cars would make things easier for me.	.96	.84	.93	.93	
I would find autonomous cars useful.	.92	.85	.78	.84	
Privacy Concerns	α =.90 AVE =.72	α =.88 AVE =.69	α =.91 AVE =.72	α =.87 AVE =.67	Malhotra et al. (2004)
Autonomous cars can cause serious personal data privacy problems.	.86	.81	.82	.79	
I am very concerned with personal data privacy issues related to autonomous cars.	.96	.96	.99	.94	
Personal data privacy related to autonomous cars is very important.	.61	.60	.62	.54	
I am concerned about threats that autonomous cars may cause to my personal data privacy.	.88	.89	.92	.901	
Trusting beliefs – Functionality	α =.94 AVE =.85	α =.80 AVE =.61	α =.83 AVE =.62	α =.80 AVE =.60	Mcknight et al. (2011)
Autonomous cars have the functions I need.	.94	.90	.89	.90	
Autonomous cars have the functions required for my tasks.	.94	.80	.78	.84	
Autonomous cars have the ability to do what I want them to do.	.87	.61	.71	.60	
Trusting beliefs– Reliability	α =.91 AVE =.72	α =.86 AVE =.61	α =.84 AVE =.59	α =.85 AVE =.58	Mcknight et al. (2011)
Autonomous cars are very reliable.	.89	.88	.85	.84	
Autonomous cars do not	.89	.87	.93	.92	

fail me.					
Autonomous cars are extremely dependable.	.94	.89	.94	.92	
Autonomous cars do not malfunction for me.	.70	.60	.44	.52	
Trusting beliefs – Helpfulness	α =.92 AVE =.75	α =.78 AVE =.51	α =.79 AVE =.49	α =.83 AVE =.57	Mcknight et al. (2011)
Autonomous cars supply my need for help through a help function.	.88	.55	.75	.62	
Autonomous cars provide competent guidance (as needed) through a help function.	.85	.63	.69	.73	
Autonomous cars provide whatever help I need.	.83	.84	.69	.82	
Autonomous cars provide very sensible and effective advice, if needed.	.90	.71	.68	.81	
Well-being	α =.96 AVE =.88	α =.87 AVE =.71	α =.90 AVE =.76	α =.90 AVE =.77	Diener (1984) and Diener and Chan (2011)
Autonomous cars would improve my life quality to ideal.	.95	.80	.82	.82	
Autonomous cars would improve my feelings of well-being.	.97	.94	.93	.97	
Autonomous cars would improve my feelings of happiness.	.89	.78	.85	.83	
Behavioral intention of use	α =.88 AVE =.80	α =.90 AVE =.82	α =.88 AVE =.78	α =.92 AVE =.85	Kulviwat et al., (2007)
Assuming I have access to autonomous cars in the future, the probability that I would use it is unlikely/likely	.94	.97	.91	.98	
Assuming I have access to autonomous cars in the future, the probability that I would use it is impossible/possible	.84	.84	.87	.86	

Table 38 Discriminant validity- Study 1, panel survey (N=331)

	M	SD	EE	PE	PC	F	R	H	WB	INT
EE	4.23	1.43								
PE	4.12	1.67	.71							
PC	4.93	1.38	.24	.25						
F	4.21	1.53	.68	.81	.28					
R	3.90	1.36	.66	.75	.33	.69				
H	4.16	1.37	.61	.81	.23	.76	.68			
WB	3.52	1.70	.62	.82	.33	.77	.75	.70		
BIU	3.99	2.06	.66	.77	.26	.76	.67	.67	.80	

EE=effort expectancy; PE=performance expectancy; BIU= behavioral intention to use; WB= well-being; H=helpfulness; F= functionality; R= reliability; PC= privacy concerns.

Table 39 Discriminant validity - Study 2, Suvery Before Driving Experience with level 2 (BDE) (N=138)

	M	SD	EE	PE	PC	F	R	H	WB	INT
EE	5.00	1.04								
PE	5.26	1.06	.64							
PC	4.39	1.60	.09	.14						
F	5.19	1.01	.57	.76	.16					
R	4.32	1.22	.25	.50	.33	.49				
H	4.95	.98	.23	.33	.14	.37	.34			
WB	4.01	1.35	.44	.73	.12	.52	.49	.38		
BIU	5.89	1.33	.49	.64	.23	.56	.40	.15	.57	

EE=effort expectancy; PE=performance expectancy; BIU= behavioral intention to use; WB= well-being; H=helpfulness; F= functionality; R= reliability; PC= privacy concerns.

Table 40 Discriminant validity - Study 3, after level 2 driving (N=138)

	M	SD	EE	PE	PC	F	R	H	WB	INT
EE	5.58	.90								
PE	5.38	1.09	.44							
PC	4.15	1.63	.14	.07						
F	5.63	.86	.64	.53	.21					
R	4.56	1.16	.56	.59	.25	.57				
H	4.92	.86	.29	.38	.11	.50	.34			
WB	4.21	1.43	.44	.75	.06	.45	.52	.45		

BIU	6.20	1.10	.61	.52	.33	.68	.57	.12	.47	

EE=effort expectancy; PE=performance expectancy; BIU= behavioral intention to use; WB= well-being; H=helpfulness; F= functionality; R= reliability; PC= privacy concerns.

Table 41 Discriminant validity - Study 4, after level 5 driving (N=138)

	M	SD	EE	PE	PC	F	R	H	WB	INT
EE	5.33	.94								
PE	5.36	1.15	.51							
PC	4.16	1.50	.21	.11						
F	5.36	.89	.48	.76	.09					
R	4.70	1.19	.43	.61	.16	.69				
H	4.64	1.06	.22	.43	.14	.47	.47			
WB	3.99	1.49	.48	.77	.10	.65	.61	.45		
BIU	5.95	1.32	.60	.59	.12	.60	.47	.21	.64	

EE=effort expectancy; PE=performance expectancy; BIU= behavioral intention to use; WB= well-being; H=helpfulness; F= functionality; R= reliability; PC= privacy concerns.

Table 42 Measurement model fit indices

	χ^2	df	RMSEA	CFI	TLI
Study 1, survey	718	295	.06	.96	.95
Study 2, before driving experience	443	296	.06	.94	.92
Study 3, level 2	506	296	.07	.92	.91
Study 4, level 5	510	296	.07	.92	.90

4. Results

4.1. Study 1: Online Survey

To test our hypotheses, we conducted a structural equation model (SEM) with members of the representative German sample, who were recruited through a professional panel provider (N=331). The results show that effort expectancy has a significant positive effect on performance expectancy (b=.78, p<.001) (Table 43). Thus, H1 is supported. In support of H2, performance expectancy has a positive effect on the behavioral intention to use fully autonomous cars (b=.24, p<.001). In addition, effort expectancy does not have a significant effect on well-being (b=.01, p>.05). Thus, 3a is not supported. However, performance expectancy has a positive effect on well-being (b=.40, p<.001). Thus, H3b is supported. In line with H4, well-being has a positive significant effect on the behavioral intention to use fully autonomous cars (b=.48, p<.001). Concerning trusting beliefs, in line with H5a, functionality has a significant positive effect on the behavioral intention to use fully autonomous cars (b=.29; p<.001). Helpfulness does not have a significant effect on the behavioral intention to use fully autonomous cars (b=.01, p>.05); thus, H5b is not supported. Additionally, reliability does not have a significant effect on the behavioral intention to use fully autonomous cars; thus, H5c is not supported (b=.08, p>.05).

Regarding the effects of trusting beliefs on well-being, the results show that functionality has a positive significant effect on well-being (b=.23, p<. 001). Additionally, helpfulness (b=.13, p<.05) and reliability (b=.26, p<.001) have a positive significant effect on well-being. Thus, H6 a, b and c are supported. To conclude, the results show that privacy concerns do not have a significant effect on the behavioral intention to use fully autonomous cars (b=-.01, p>.05). Thus, H7a is not supported. However, privacy concerns have a significant effect on well-being (b=-.08, p<.05); thus, H7b is supported.

Table 43 Results of the model estimation of study 1

Hypotheses	***b***	**Supported/Not supported**
EE→ PE	.78***	H1 : supported
PE → BIU	.24**	H2 : supported
EE → WB	.01 ns	H3a : not supported
PE → WB	.40***	H3b : supported
WB → BIU	.48***	H4 : supported
F → BIU	.29***	H5a : supported
H → BIU	.01ns	H5b : not supported

R → BIU	.08ns	H5c : not supported
F → WB	.23***	H6a : supported
H → WB	.13*	H6b : supported
R → WB	.26***	H6c : supported
PC → BIU	.01ns	H7a : not supported
PC → WB	-.08*	H7b : supported

EE=effort expectancy; PE=performance expectancy; BIU= behavioral intention to use; WB= well-being; H=helpfulness; F= functionality; R= reliability; PC= privacy concerns.
***p < .001, **p < .01, *p < .05, ns: not significant

In addition, we conducted a mediation analysis (Table 44), the results of which show that effort expectancy has a significant indirect positive effect on the behavioral intention to use fully autonomous cars via performance expectancy (b = .18, p<.05, 95% CI [.0551, .3215]). The indirect effect of effort expectancy on the behavioral intention to use fully autonomous cars via well-being is not significant (b = .00, p>.05, 95% CI [-.0393, .0554]). However, effort expectancy has an indirect effect on the behavioral intention to use fully autonomous cars via performance expectancy and well-being (b = .15, p<.001, 99.9% CI [.0478, .2790]). In addition, the results show that privacy concerns have a significant negative effect on the behavioral intention to use fully autonomous cars via well-being (b = -.04, p<.05, 95% CI [-.0814, -.0014]). Concerning the indirect effects of trusting beliefs, functionality has an indirect positive effect on the behavioral intention to use fully autonomous cars via well-being (b = .11, p<.01, 99% CI [.0418, .1871]); helpfulness has an indirect positive effect on the behavioral intention to use fully autonomous cars via well-being (b = .06, p<.05, 95% CI [.0022, .1254]); and reliability has a positive significant indirect effect on the behavioral intention to use fully autonomous cars via well-being (b = .12, p<.001, 99.9% CI [.0195, .2598]).

Table 44 Results of mediation analysis of study 1

	Effect	95% CI		99% CI		99.9% CI	
		Lower	Upper	Lower	Upper	Lower	Upper
Total indirect EE	.34***	.1959	.4919	.1539	.5459	.1075	.5986
EE + PE + BIU	.18**	.0551	.3215	.0128	.3690	-.0453	.4147
EE + WB + BIU	.00ns	-.0393	.0554	-.0601	.0748	-.0780	.0892
EE + PE + WB + BIU	.15***	.0853	.2233	.0710	.2483	.0478	.2790
PC + WB + BIU	-.04*	-.0814	-.0014	-.0985	.0093	-.1170	.0214
F + WB + BIU	.11**	.0418	.1871	.0173	.2158	-.0077	.2599
H + WB + BIU	.06*	.0022	.1254	-.0148	.1439	-.0356	.1826
R + WB + BIU	.12***	.0552	.1962	.0351	.2304	.0195	.2598

EE=effort expectancy; PE=performance expectancy; BIU= behavioral intention to use; WB= well-being; H=helpfulness; F= functionality; R= reliability; PC= privacy concerns. ***p < .001, **p < .01, *p < .05, ns: not significant

4.2. Study 2: Replication Study

We replicated most of the results of Study 1 by testing the model with a second sample (N=138) through structural equation modeling (SEM) (Table 45). In line with Study 1, the results show that effort expectancy has a significant positive effect on performance expectancy (b=.54, p<.001). Again, H1 is supported. Additionally, performance expectancy has a significant positive effect on the behavioral intention to use fully autonomous cars (b=.30, p<.05). Thus, H2 is again supported. Effort expectancy does not have a significant effect on well-being (b=.10, p>.05). As in Study 1, H3a is not supported. However, performance expectancy has a positive significant effect on well-being (b=.57, p<.001); thus, in line with Study 1, H4b is supported. Well-being has a significant positive effect on the behavioral intention to use fully autonomous cars (b=.27, p<.01). Thus, H4 is supported again. Concerning trusting beliefs, the results show that functionality has a significant positive effect on the behavioral intention to use fully autonomous cars (b=.30, p<.01). Thus, in line with Study 1, H5a is supported. Helpfulness does not have a significant effect on the behavioral intention to use fully autonomous cars (b=-.13, p>.05). Again, H5b is not supported. Reliability does not have a significant effect on the behavioral intention to use fully autonomous cars (b=.02, p<.05). Thus, in line with Study 1, H5c is not supported. Regarding the relationship between trusting beliefs and well-being, functionality does not have a significant effect on well-being (b=.02, p>.05); thus, contrary to Study 1, H6a is not supported. The effect of helpfulness on well-being is almost significant (b=.19, p<.10); thus, H6b is almost supported. Consistent with Study 1, reliability has a significant effect on well-being (b=.20, p<.05). Thus, again, H6c is supported. Concerning privacy concerns, they have a significant negative effect on the behavioral intention to use fully autonomous cars (b=-.15, p<.01); thus, contrary to Study 1, H7a is supported. However, the effect of privacy concerns on well-being is not significant (b=.01, p>.05). Thus, H7b is not supported.

Table 45 Result of the model estimation of study 2

Hypotheses	**b**	**Supported/ Not supported**
EE → PE	.54***	H1 : supported
PE → BIU	.30*	H2 : supported
EE → WB	.10 ns	H3a : not supported
PE → WB	.57***	H3b : supported
WB → BIU	.27**	H4 : supported
F → BIU	.30**	H5a : supported
H → BIU	-.13ns	H5b : not supported
R → BIU	.02ns	H5c : not supported
F → WB	.02ns	H6a : not supported
H → WB	$.19^{\dagger}$	H6b : partially supported
R → WB	.20*	H6c : supported
PC → BIU	-.15**	H7a : supported
PC → WB	.01ns	H7b : not supported

EE=effort expectancy; PE=performance expectancy; BIU= behavioral intention to use; WB= well-being; H=helpfulness; F= functionality; R= reliability; PC= privacy concerns.
***p < .001, **p < .01, *p < .05, ns: not significant

From the mediation analysis (Table 46), the results show that effort expectancy once again has an indirect effect on the behavioral intention to use fully autonomous cars via performance expectancy (b = .16, p<.01, 99% CI [.0148, .3760]). Consistent with Study 1, the indirect effect of effort expectancy on the behavioral intention to use fully autonomous cars via well-being is not significant (b = .03, p>.05, 95% CI [-.0316, .1146]). However, in line with Study 1, effort expectancy has an indirect effect on the behavioral intention to use fully autonomous cars via performance expectancy and well-being (b = .08, p<.01, 99% CI [.0297, .1458]). In contrast to Study 1, the results show that privacy concerns do not have a significant effect on the behavioral intention to use fully autonomous cars via well-being (b = .00, p>.05, 95% CI [-.0321, .0363]). Regarding trusting beliefs, functionality does not have an indirect significant effect on the behavioral intention to use fully autonomous cars via well-being (b = .01, p>.05, 95% CI [-.0685, .0890]). Additionally, helpfulness does not have an indirect significant effect on the behavioral intention to use fully autonomous cars via well-being (b = .05, p>.05, 95% CI [-.0149, .1421]). Only reliability has a positive significant indirect effect on the behavioral intention to use fully autonomous cars via well-being (b = .06, p<.05, 95% CI [.0070, .1224]).

Table 46 Results of mediation analysis of Study 2

	Effect	**95% CI**		**99% CI**		**99.9% CI**	
		Lower	Upper	Lower	Upper	Lower	Upper
Total indirect EE	.27***	.1189	.4673	.0810	.5527	.0295	.6271
EE + PE + BIU	.16**	.0473	.3192	.0148	.3760	-.0374	.4648
EE + WB + BIU	.03ns	-.0316	.1146	-.0522	.1492	-.0829	.1891
EE + PE + WB + BIU	.08**	.0297	.1458	.0161	.1819	-.0233	.2191
PC + WB + BIU	.00ns	-.0321	.0363	-.0480	.0508	-.0731	.0740
F + WB + BIU	.01ns	-.0685	.0890	-.1064	.1326	-.1996	.1829
R + WB + BIU	.06*	.0070	.1224	-.0073	.1485	-.0321	.1944
H + WB + BIU	.05ns	-.0149	.1421	-.0338	.1924	-.0791	.2241

EE=effort expectancy; PE=performance expectancy; BIU= behavioral intention to use; WB= well-being; H=helpfulness; F= functionality; R= reliability; PC= privacy concerns
***p < .001, **p < .01, *p < .05, ns: not significant

4.3. ANOVA Analyses with Repeated Measures for Studies 2 through 4

Once the model was tested and validated in Study 1 and Study 2, we answered our research questions by further analyzing how consumers' perceptions of fully autonomous vehicles change according to the different levels of automation. To investigate the evolutions of trusting beliefs, well-being, privacy concerns and the behavioral intention to use fully autonomous cars across the different levels of automation, we conducted an ANOVA with repeated measures to compare consumers' perceptions toward fully autonomous cars before their driving experience (BDE), after their experience with a semiautonomous car (level 2) and after their experience with a fully autonomous car (level 5) (Table 47). In particular, we conducted a Bonferroni test to conduct multiple comparisons of each construct within the different levels.

The results show that effort expectancy significantly increases from before the driving experience to the experience with level 2 automation ($M_{Level2} – M_{BDE}$ = .58 p<.001) and from before the driving experience to the experience with level 5 automation ($M_{Level5} – M_{BDE}$=.33, p<.01). However, from level 2 to level 5, effort expectancy significantly decreased (M_{Level5} - M_{Level2} =-.25, p<.01). Performance expectancy is not differently perceived before or after experiencing level 2 ($M_{Level2} – M_{BDE}$ =.12, p>.05), before experiencing level 2 or after experiencing level 5 (M_{Level5} - M_{Level2} =-.01, p>.05), or before the driving experience and after experiencing level 5 ($M_{Level5} – M_{BDE}$ =-.10, p>.05). Concerning trusting beliefs, the results show that functionality does not significantly change from before the driving experience to the experience with level 2 ($M_{Level2} – M_{BDE}$= .17, p>.05), from level 2 to level 5 (M_{Level5} - M_{Level2} = -.00, p>.05) or from before the driving experience to the experience with level 5 ($M_{Level5} – M_{BDE}$ = .17, p>.05). There is no significant difference in helpfulness from before the driving experience to the experience with level 2 ($M_{Level2} – M_{BDE}$ =-.03, p>.05). However, helpfulness decreases from level 2 to level 5 (M_{Level5} - M_{Level2} =-.28, p<.001). In addition, consumers' perception of helpfulness decreases from before the driving experience to the experience at level 5 ($M_{Level5} – M_{BDE}$ =.31, p<.001). Perception of reliability significantly increases from before the driving experience to the experience with level 2 ($M_{Level2} – M_{BDE}$ =.24, p<.05). It also increases from before the driving experience to the experience with level 5 ($M_{Level5} – M_{BDE}$=.38, p<.05). However, it does not significantly change from level 2 to level 5 (M_{Level5} - M_{Level2} =.15, p>.05). The privacy concerns, in contrast, decrease from before the driving experience to the experience with level 2 ($M_{Level2} – M_{BDE}$ =-.24, p<.001) and from before the driving experience to level 5 ($M_{Level5} – M_{BDE}$ =-.23, p<.001). However, they remain unchanged from level 2 to level 5 (M_{Level5} - M_{Level2} =.01, p>.05). Well-being significantly increases from before the driving experience to the experience with level 2 ($M_{Level2} – M_{BDE}$ =.20, p<.01). However, it significantly decreases from level 2 to level 5 (M_{Level5} - M_{Level2} =-.23, p<.05). Additionally, it remains unchanged from before the driving experience to the experience with level 5 ($M_{Level5} – M_{BDE}$ = -.02 ns, p<.01). Consistent with well-being, the behavioral intention to use fully autonomous cars significantly increases from before the driving experience to the experience with level 2 ($M_{Level2} – M_{BDE}$ =.31, p<.01). However, the behavioral intention to use fully autonomous cars significantly decreases from level 2 to level 5 (M_{Level5} - M_{Level2} =-.25, p<.01). Additionally, it remains unchanged from before the driving experience to the experience with level 5 ($M_{Level5} – M_{BDE}$ = -.06 ns, p>.05).

Table 47 Results of Anova with repeated measures

C	Level	M	SD	Bonferroni	F	PES
EE	BDE	5.00	1.04	$M_{Level2} – M_{BDE}$ = .58***	F(1.79,244.49)=25.70***	.16
	2	5.58	.90	M_{Level5} - M_{Level2} = -.25**		
	5	5.33	.94	$M_{Level5} – M_{BDE}$ = .33**		

PE	BDE	5.26	1.06	$M_{Level2} - M_{BDE} = .12$ns	$F(2, 274)=1.60$ns	.01
	2	5.38	1.09	$M_{Level5} - M_{Level2} = -.01$ns		
	5	5.36	1.15	$M_{Level5} - M_{BDE} = .10$ns		
F	BDE	5.19	1.01	$M_{Level2} - M_{BDE} = .17$ns	$F(1.91, 261.33)=3.59$*	.03
	2	5.36	.86	$M_{Level5} - M_{Level2} = -.00$ns		
	5	5.36	.89	$M_{Level5} - M_{BDE} = .17$ns		
H	BDE	4.95	.98	$M_{Level2} - M_{BDE} = -.03$ns	$F(1.70,233.46)=9.08$***	
	2	4.92	.86	$M_{Level5} - M_{Level2} = -.28$***		
	5	4.64	1.06	$M_{Level5} - M_{BDE} = .31$**		
R	BDE	4.32	1.22	$M_{Level2} - M_{BDE} = .24$*	$F(2, 274)=11.33$***	.08
	2	4.56	1.16	$M_{Level5} - M_{Level2} = .15$ns		
	5	4.70	1.19	$M_{Level5} - M_{BDE} = .38$***		
PC	BDE	4.39	1.60	$M_{Level2} - M_{BDE} = -.24$***	$F(1.89, 258.88)=8.85$***	.06
	2	4.15	1.63	$M_{Level5} - M_{Level2} = .01$ns		
	5	4.16	1.50	$M_{Level5} - M_{BDE} = -.23$**		
WB	BDE	4.01	1.35	$M_{Level2} - M_{BDE} = .20$**	$F(1.87,256.62)=5.15$**	.04
	2	4.21	1.43	$M_{Level5} - M_{Level2} = -.23$*		
	5	3.99	1.49	$M_{Level5} - M_{BDE} = -.02$ns		
BIU	BDE	5.89	1.33	$M_{Level2} - M_{BDE} = .31$***	$F(1.89,259.17)=10.18$***	.07
	2	6.20	1.10	$M_{Level5} - M_{Level2} = -.25$**		
	5	5.95	1.32	$M_{Level5} - M_{Level0} = .06$ns		

C= construct; PES= partial eta squared; BDE= before driving experience; EE=effort expectancy; PE=performance expectancy; BIU= behavioral intention to use; WB= well-being; H=helpfulness; F= functionality; R= reliability; PC= privacy concerns
***p < .001, **p < .01, *p < .05, ns: not significant

4.4. Study 2 and Study 3: Within-Participant Statistical Mediation Analysis

Drawing from Montoya and Hayes (2017), we then conducted a mediation analysis with repeated measures by using the SPSS macro (Table 48). Building on Judd et al. (2001), Montoya and Hayes (2017) address statistical mediation analysis in the two-condition within-participant design. By using a path-analytic approach, the authors provide a method to estimate the indirect effects of a within-participant manipulation on a dependent variable (Montoya and Hayes 2017). This analytical approach allowed us to test how the relationships between variables change after participants experienced different levels of automation. In this way, we were able to capture the evolution of the effects of trusting beliefs, privacy concerns and subjective well-being on the behavioral intention toward fully autonomous cars, while accounting for the different levels of automation.

First, we investigated how the relationships between variables changed between before the driving experience (BDE) and after experiencing the semiautonomous car (level 2) (Table 48). The results show that the effect of effort expectancy on performance expectancy is not significantly augmented from before the driving experience to the experience with level 2 automation (diff=.07, $p>.05$). Additionally, the effect of performance expectancy (diff=.07, $p>.05$) and well-being on the behavioral intention to use (diff=.08, $p>.05$) is not significantly augmented. We also find no significant difference in the effect of performance expectancy on well-being before the driving experience and after the experience with level 2 (diff=.07, $p>.05$), in the effect of functionality on well-being (diff=.11, $p>.05$), or in the effect of helpfulness on well-being (diff=.01, $p>.05$). However, the effect of reliability on well-being significantly increases from before the driving experience to the experience with level 2 (diff=.16, $p<.05$). In addition, the effect of functionality on the behavioral intention to use significantly increases from before the driving experience to the experience with level 2 (b=.14, $p<.01$). However, the effect of reliability and helpfulness on the behavioral intention to use does not significantly increase from before the driving experience to the experience with level 2 (diff=.03, $p>.05$; diff=-.12, $p>.05$). To conclude, the effect of privacy concerns on the behavioral intention to use and well-being remain unchanged from before the driving experience to the experience with level 2 (diff=.00, $p>.05$; diff=.01, $p>.05$; diff=.02, $p>.05$).

Table 48 Results of the repeated measure analysis: from Before the Driving Experience (BDE) to the experience with level 2

Relationships	diff
EE → PE	.07ns
PE → BIU	.07ns
WB → BIU	.08ns
EE → WB	.07 ns
PE → WB	.15ns
F → BIU	.14*
R → BIU	.03ns
H → BIU	-.12ns
F → WB	.11ns
R → WB	.16*
H → WB	.01 ns
PC → BIU	.00 ns
PC → WB	.02 ns

EE=effort expectancy; PE=performance expectancy; BIU= behavioral intention to use; WB= well-being; H=helpfulness; F= functionality; R= reliability; PC= privacy concerns.
***p < .001, **p < .01, *p < .05, ns: not significant

Regarding the mediation effect, we find only an almost significant indirect effect of driving experience on the behavioral intention to use via functionality (b = .02, 90% CI [.0016, .0638]; 95% CI [-.0011, .0738]) (Figure 25).

Figure 25 Mediation analysis with repeated measures with Before the Driving Experience (BDE) and level 2

† p<.10

4.5. Study 3 and Study 4: Within-Participant Statistical Mediation Analysis

Next, we conducted an additional mediation analysis with repeated measures using the SPSS macro to investigate how consumers' perceptions change between the driving experience with level 2 automation and the driving experience with level 5 (Table 49). The results show that from experiencing level 2 to experiencing level 5, the effect of effort expectancy on performance expectancy is not significantly different (diff=.06, p>.05). Additionally, the effect of performance expectancy (diff=.06, p>.05) and the effect of well-being on the behavioral intention to use fully autonomous cars (diff=.03, p>.05) remain unchanged. However, from level 2 to level 5, the effect of effort expectancy and performance expectancy on well-being is significantly augmented (diff=.31, p<.01; diff=.28, p<.01). Concerning the effect of trusting beliefs on the behavioral intention to use fully autonomous cars, from level 2 to level 5, the effect of functionality significantly increases (diff=.25, p<.01), and the effect of reliability also significantly increases (b=.23, p<.01). However, there was no significant difference in the effect of helpfulness on the behavioral intention to use fully autonomous cars (diff=-.17, p>.05). Concerning the effect of trusting beliefs on well-being, only the effect of helpfulness on well-being significantly increases (diff=.28, p<.01). In fact, from level 2 to level 5, there is no significant difference in the effect of functionality on well-being (diff=.13, p>.05) or reliability on well-being (diff=.00, p>.05). In addition, from experiencing level 2 to level 5, the effect of privacy concerns on the behavioral intention to use fully autonomous cars remains unchanged (b=-.15, p>.05). However, the effect of privacy concerns on well-being decreases (b=-.20, p<.05).

Table 49 Results of the repeated measure analysis with level 2 and level 5

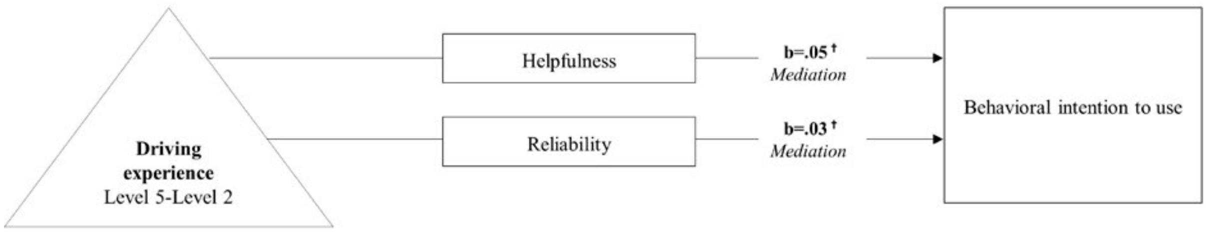
Relationships	diff
EE → PE	.06ns
PE → BIU	.06ns

WB → BIU	.03ns
EE → WB	.31**
PE → WB	.28**
F → BIU	.25**
H → BIU	-.17ns
R → BIU	.23**
F → WB	.13ns
H → WB	.28**
R → WB	.00ns
PC → BIU	-.15ns
PC → WB	-.20*

EE=effort expectancy; PE=performance expectancy; BIU= behavioral intention to use; WB= well-being; H=helpfulness; F= functionality; R= reliability; PC= privacy concerns.
***p < .001, **p < .01, *p < .05, ns: not significant

Concerning the mediation effects, we found an almost significant indirect effect of driving experience on behavior intention to use fully autonomous cars via helpfulness (b = .05, 90% CI [.0012, .1098] 95% CI [-.0055, .1266) and via reliability (b = .03, 90% CI [.0033, .0716]; 95% CI [-.0018, .0795) (Figure 26).

Figure 26 Mediation analysis with repeated measures with level 2 and level 5



p<.10

5. General Discussion

Despite the growing research focusing on consumer perceptions of autonomous cars (Bertrandias et al. 2021; Gurumurthy and Kockelman 2020; Huang and Qian 2021), only a few studies have investigated how consumers' beliefs change when experiencing different levels of automation (e.g. Eggers and Eggers 2021). We suggest that adopting a more dynamic approach by investigating experience with a technology across different levels of automation is important to comprehend how consumers' perceptions and evaluations of a product evolve according to the different development stages of its technology. For instance, the increase in perceived complexity of the autonomous functions from level-2 to level-5 automation could decrease consumers' usage intentions if they are not familiar with them and perceive them as difficult to use (Hartwich et al. 2018). On the other hand, a lack of functionalities at lower levels could decrease consumers' intention to use them, as they might be perceived to be less reliable than higher levels of automation. However, trying and experiencing new technological features can help create stronger beliefs about a technology among consumers, who, as a direct result of such experiences, are able to better comprehend the product (Kempf 1999; Smith 1993). In this regard, we suggest that experience with different automation stages can be a key factor in comprehending consumers' usage intentions of autonomous vehicles, thereby contributing to innovation management research (Rödel et al. 2014).

Thus, by using a rare multidesign method that combines an online survey with a field study and a simulator study, this paper sheds light on how consumers' trusting beliefs, perceived well-being, privacy concerns and behavioral intention to use fully autonomous cars evolve when they experience increasing levels of automation. We first tested the theoretical model with a representative sample through an online survey, highlighting the importance of cognitive variables, namely, effort and performance expectancy, trusting beliefs of functionality, helpfulness, reliability and privacy concerns, in affecting consumers' well-being and behavioral intention to use. Next, we replicated most of the results among another within-subject sample of users, who expressed their perceptions before and after their usage of a level-2 AV and a level-5 AV. Finally, based on the within-subject field and simulator studies, we showed how consumers' beliefs change when they experience different levels of automation; in this case, levels 2 and 5 (SAE International 2016). Conducting a field and simulator study is useful for addressing two of the main limitations of the extant academic research on autonomous vehicles: first, the lack of empirical investigations that aim to understand consumers' attitudes, perceptions and behaviors according to different levels of automation and development stages of autonomous cars (Huang and Qian 2021); second, the limitations of declarative, survey-based methodologies (Gallup 1988). In this regard, above all, when investigating disruptive innovations, declarative surveys and their associated scenarios might fail to properly contextualize a new technological product to give an accurate overview of the evolution of consumers' perceptions. To overcome these issues, field studies have been largely used in marketing research and applied to technology usage (e.g. Gneezy 2017; Li and Kannan 2014; Yousafzai et al. 2005). These studies suggest that direct experiences through field experimentations and product trials are stronger and better predictors of consumers' behaviors than indirect experiences through scenarios and surveys, which might be too abstract to evaluate disruptive technologies that are not still on the market, such as fully autonomous level-5 cars (Kempf 1999; Smith 1993). Additionally, simulation studies have been shown to be a safer and more efficient way to test new disruptive technological products, allowing simulations of numerous different real-world scenarios while creating environments that consumers can personally and directly experience and feel

(Dosovitskiy et al. 2017). In addition, a simulation study facilitates the testing of fully autonomous driving without driver intervention, which aligns with current legislation.

5.1. Validating the Model

We validated our conceptual model in Study 1, replicating most of the results in Study 2 before participants' experience with the semiautonomous level-2 car. Consistent with Venkatesh et al. (2003, 2011), the results suggest that before experiencing a new technology in scenario-based settings, performance expectancy is a significant driver of consumers' behavioral intention to use fully autonomous cars. In this regard, the utilitarian value of AV in terms of driving performance plays a significant role in determining consumers' usage intentions of fully autonomous cars before experiencing the new technology. In addition, in line with the literature, we show that the more autonomous functions are perceived as easy to use, the better consumers' predicted performance of a car, increasing their usage intentions (Kaur and Rampersad 2018; Venkatesh 2000). Thus, when automated functions are perceived to be less difficult to use, the technology is considered more useful. In addition, in line with Lu et al. (2021) and Martínez-Caro et al. (2018), the results suggest that consumers' performance expectancy also has a significant effect on their subjective well-being, which is a strong driver of adoption. Thus, we suggest that successful driving performance might relieve consumers of the stress related to driving tasks, offering a more pleasant and enjoyable driving experience. In addition, in line with a growing stream of research, we underscore the importance of an increase in consumers' perceived subjective well-being in their behavioral intentions to use new technologies (Bertrandias et al. 2021; Munzel et al. 2018). In fact, autonomous cars represent a potentially disruptive yet beneficial change to transportation systems, having the potential to increase consumers' quality of life and perception of well-being due to their automated driving performance (Fagnant and Kockelman 2015).

Accordingly, our results show that the more a car is perceived as capable of increasing consumers' well-being, the more inclined they are to drive it. However, the results also show that the ease of use associated with automated functions does not increase consumers' perceived subjective well-being. We suggest that only the degree of users' satisfaction with the performance of a technology, which is increased by the ease of use associated with the automated functions, directly enhances users' perceived quality of life and needs fulfilment (Lu et al. 2021; Martínez-Caro et al. 2018).

In addition, in line with the literature, the results suggest that consumers' well-being is decreased by privacy concerns (Anderson et al. 2013; Petty 2000). Their lack of control over personal information may engender negative feelings and diminish consumers' perceived quality of life (André et al. 2018; Du and Xie 2020). As a consequence, privacy concerns also negatively affect consumers' behavioral intention to use a new technology by decreasing their perceived subjective well-being (Angst and Agarwal 2009; Dinev and Hart 2006; Gurumurthy and Kockelman 2020). Addressing consumers' privacy concerns can be a key factor to increase adoption and postadoption behaviors by decreasing consumers' negative feelings. Some examples of privacy issues to address include the perceived threat of the unauthorized use of information about the driver and car's route, hacker attacks on a system and driver monitoring (Bertrandias et al. 2021).

In addition to the utilitarian value of autonomous functions, the trusting beliefs of helpfulness, functionality, and reliability also increase consumers' subjective well-being (Helliwell and Huang 2011; Michalos 1990; Poulin and Haase 2015). Thus, the more individuals perceive a technology to be predictable, functional and helpful in executing their driving tasks, the more their perceptions of happiness and life satisfaction are fulfilled, thereby increasing individuals' intention to use the technology. We suggest that trusting beliefs foster a more enjoyable driving experience by decreasing consumers' perceptions of uncertainty and vulnerability and increasing their acceptance of fully autonomous cars (Poulin and Haase 2015; Sirgy et al. 2012). Concerning the direct effect of trusting beliefs on consumers' behavioral intention to use fully autonomous cars, only functionality has a significant direct effect on their intention to use the new technology. In this regard, functionality refers to the degree to which an individual believes the technology has the functions or features needed to accomplish one's driving tasks (McKnight 2005). Consistent with previous research, the more a car is perceived to be able to execute tasks that meet users' expectations, the more individuals trust the AV system and seek to adopt it (Kaur and Rampersad, 2018; Mcknight et al. 2011). However, in contrast to our assumptions, reliability and helpfulness do not significantly directly affect consumers' behavioral intention to use fully autonomous cars. We suggest that a certain degree of uncertainty still characterizes highly disruptive autonomous technologies and algorithms, which are often not clear or transparent in consumers' minds (Hohenberger et al. 2017). Above all, as autonomous driving technology is still evolving and often perceived to be unpredictable in many situations (Bonnefon et al. 2016), consumers still struggle to consider the technology reliable enough to be adopted. Moreover, individuals are not yet fully aware of the abstract and intangible autonomous car functions because they may lack the experience necessary to comprehend the potential of these functions to provide adequate and responsive assistance. For this reason, helpfulness is still not a direct driver of consumers' intention to use fully autonomous cars (Hengstler et al. 2016; Kaur and Rampersad 2018).

5.2. Experience with Increased Levels of Automation: Performance Expectancy and Effort Expectancy

The results from the repeated ANOVA show that as automation increases from level 2 to level 5, functions might be perceived by users as more difficult to use. This perception of an increased degree of complexity of functions could negatively affect consumers' behavioral intentions. However, experiencing autonomous functions might be a solution to compel individuals to perceive them to be easier to use and make them appear to be less abstract. In fact, when comparing consumers' perceptions of effort expectancy before their driving experience with their perceptions after experiencing level-2 automation, the ease of use they associate with the technology increases. The result is the same when comparing consumers' perceptions of effort expectancy before their driving experience with their perceptions after experiencing level 5. As Venkatesh et al. (2011, p. 528) suggest, "user expectations about the effort required to use a system are subject to change after usage because such a belief can only be well formed based on hands-on experience" (Venkatesh et al. 2011; Venkatesh and Davis 1996). Accordingly, we empirically show, for the first time, in the context of autonomous vehicles, how consumers' experience with this technology fundamentally shapes their perceptions related to the effort to learn and use new functions.

On the one hand, the results of Study 1 and Study 2 confirm the key role of consumers' expected performance of an autonomous car in increasing their behavioral intention to use the product (Venkatesh et al. 2003, 2011); on the other hand, Studies 3 and 4 suggest that consumers' performance expectancy does not change after experiencing levels 2 and 5 of automation. In addition, the effect of performance expectancy on consumers' behavioral intention remains unchanged both before and after their driving experiences with level 2 and level 5. In this regard, although previous studies have already shown how consumers' positive beliefs related to technological performance affect behavioral intention to adopt and use fully autonomous cars (Hohenberger et al. 2017), our study highlights, for the first time, how, after consumers' experience different levels of automation, 1) their expected performance of AV functions does not increase and 2) this performance expectancy's effect on consumers' behavioral intention does not increase. Thus, while performance expectancy is still an important driver of consumers' usage intentions in influential survey- and scenario-based studies, consumers' actual experience of the functions does not improve AV perceived performance or its effect on consumers' behavioral intention to use the technology. We suggest that after experiencing the functions of level-2 and level-5 automation, individuals might become accustomed to the AV performance, do not increasing their usage intention. Accordingly, research shows that when using a new technological product, different stages of the development or use of the technology engender different forms of expectation (Saborowski and Kollak 2015). The more customers use a technology, the more they can become accustomed to its functions and its performance (Saborosky and Kollak 2015). However, though the effect of performance expectancy on adoption does not increase after experiencing higher levels of automation, the results suggest that after experiencing levels 2 to 5, the effect of performance expectancy and effort expectancy on consumers' well-being significantly increases. These findings are unique and new, as we show, for the first time, that after experiencing autonomous functions, their perceptions related to a car's performance and its facility of usage increase their subjective well-being. The more individuals experience AV, the more they generate favorable perceptions of it, thereby reducing uncertainty about the performance of and the effort required by the technology, thus potentially increasing their positive feelings (Venkatesh et al. 2011). Well-being is thus an absolutely crucial concept in new, disruptive technology adoption.

5.3. Experience with Increased Levels of Automation: Trusting Beliefs

Concerning how trusting beliefs toward fully autonomous cars evolve across the different levels of automation, the results suggest that functionality does not significantly increase when comparing consumers' perceptions before their driving experience with their perceptions after experiencing level 2 and level 5. In addition, the effect of functionality on well-being remains unchanged after consumers' experience these different levels. Consistent with performance expectancy, we suggest that in the case of functionality, customers might become accustomed to a car's functions and to their performance (Saborosky and Kollak 2015). Thus, unless a critical event happens, consumers' perceptions of functionality and their effect on well-being remain stable across different automation levels. However, the positive effect of functionality on consumers' behavioral intention significantly increases from before their driving experience to their experience with level 2 and from their experience with level 2 to level 5. The more individuals experience a technology, the more likely they are to trust it to have the ability to accomplish the functionalities it promises, and the more they want to use it (McKnight et al. 2011; Venkatesh et al. 2011). Accordingly, the results show, for the first time, that functionality mediates the relationship between consumers' driving experience and their behavioral intention to use fully autonomous functions. Thus, the greater their experience with higher levels of automation, particularly with level 2, is, the higher consumers' trusting beliefs related to the functionality of an AV, which are critical for acceptance (McKnight 2011; Venkatesh et al. 2011).

Concerning the trusting belief of helpfulness, the results from the repeated ANOVA suggest that helpfulness significantly decreases when moving from level 2 to level 5. However, the mediation analysis shows that helpfulness also mediates the effect of consumers' driving experience on their behavioral intention to use. In addition, its effect on well-being increases when moving from experiencing level 2 to level 5. Thus, we suggest that on the one hand, consumers might find fully autonomous functions to be less helpful than semiautonomous functions, as they can be more complex and difficult to understand; on the other hand, this result might be due to consumers' lack of experience with fully autonomous functions in actual driving contexts. As a solution, consumers experiencing a car might actually increase its perceived helpfulness, increasing their usage behaviors (Kempf 1999; Rödel et al. 2014; Smith1993). In addition, increasing consumers' awareness about how functions might help and assist them during driving tasks, through experience, might foster their perceptions of subjective well-being, offering a more pleasant and relaxed experience (Choi and Ji 2015). In this regard, research has shown the importance of consumers trying and experiencing a new technology to comprehend its actual capabilities and potential benefits (Soscia et al., 2011, Venkatesh et al. 2011). According to Meuter et al. (2005), an innovation is triable when it allows users to observe its benefits and to gain confidence in its use (Meuter et al. 2005; Soscia et al. 2011). Thus, the present study is one of the first to suggest that an actual experience of new technology, such as driving an autonomous car, can increase consumers' perceptions of subjective well-being.

The results also highlight that independent of the level of automation, consumers' actual experience of a car is fundamental to increasing its reliability for them (McKnight 2005, 2011). Moreover, the effect of reliability on consumers' behavioral intention to use AV technology significantly increases after they experience level 5, and it mediates the relationship between their driving experience and behavioral intention to use the functions. Thus, the degree of uncertainty around autonomous technology and algorithms, which compels them to be perceived as unpredictable in many situations, decreasing consumers' behavioral intention to use (Bonnefon et al. 2016; Hohenberger et al. 2017), can be overcome by increasing consumers' experience with the technology (Hengstler et al. 2016; Kaur and Rampersad 2018; Venkatesh et al. 2011). Our results are in line with McKnight et al. (2021, p. 13), who suggest that "experience with the technology is fundamental for fostering knowledge-based trust based on trusting beliefs about characteristics of the technology itself".

In addition, the effect of reliability on well-being significantly increases after experiencing level 2. The more familiar consumers become with semiautonomous functions, the more they perceive autonomous cars to be reliable, increasing their subjective well-being. However, this effect remains unchanged after consumers' experience level 5. Thus, we suggest that since level 5 is still abstract in consumers' minds and needs to be implemented in actual situations, consumers still find it difficult to estimate how fully autonomous level-5 cars could practically increase their quality of life and perceived well-being.

5.4. Experience with Increased Levels of Automation: Well-Being, Usage Intentions and Privacy Concerns

Consistent with these findings, while consumers' perceived subjective well-being significantly increases after they experience level 2, it significantly decreases after they experience level 5. In addition, despite the key role of well-being in increasing consumers' adoption intention, its effect on their behavioral intention to use remains unchanged across the levels of automation. We suggest that even when consumers consider increased well-being an important driver of their adoption, just how higher levels of automation could increasingly benefit them in terms of an improved quality of life might not yet be clear. Consistent with their well-being, consumers' adoption intention also increases after they experience level 2, but it diminishes after they experience level 5, which shows that individuals remain skeptical about using less familiar fully autonomous cars (Eggers and Eggers 2021). Thus, we suggest that individuals might not yet be ready to adopt level-5 automation, as they do not yet comprehend its benefits to them via an increased well-being, or via level 5's ease of use, reliability, helpfulness and functionality. Consumer experiences through product trials, however, could help overcome these issues (Kempf 1999; Rödel et al. 2014; Smith 1993). In particular, our results suggest that consumers' driving experiences of AVs with fully autonomous functions could increase their intention to use them, mainly by augmenting their trusting beliefs related to consumers' perceived functionality, helpfulness and reliability of

AVs. In addition, consumers' experiences of AV functions plays a fundamental role in positively affecting consumers' perceived well-being, by decreasing consumers' privacy concerns related to the technology (Davis and Pechmann 2013; Du and Xie 2020; Wirtz and Lwin 2009). In this regard, the ANOVA through repeated measures shows that consumers' privacy concerns tend to significantly decrease when comparing consumers' perceptions before their driving experiences with their perceptions after their driving experiences with level 2 and level 5. In addition, when moving from level 2 to level 5, the negative effect of consumers' privacy concerns on their well-being decreases. Thus, we suggest that experiencing AV functions might address consumers' concerns with privacy issues, diminishing the negative feelings related to their lack of control over their personal information. Accordingly, previous research has shown that prior experience with a technology is positively associated with how sensitive people are to risks (Cho et al. 2010).

6. Theoretical Contributions

The present paper offers four main theoretical contributions. First, we aim to contribute to the emerging literature on consumer behaviors related to intelligent AI-based products and, in particular, to autonomous vehicles (Bertrandias et al. 2021; Huang and Quian 2021; Puntoni et al. 2021). In this regard, we enrich the existing literature by accounting for the complexity of a new and disruptive technology across its developmental stages. As Huang and Qian (2021) suggest, differentiating between different automation levels can help researchers better understand the potential drivers of consumer acceptance. As autonomous functions will be progressively introduced into markets, consumers will have opportunities to gradually shape and form their beliefs (Menon et al. 2020). Accordingly, in addition to elaborating consumers' perceptions toward fully autonomous cars, this study also addresses the need to investigate how gradually experiencing different levels of automation, particularly level 2 and level 5 (SAE International 2016), affects consumers' beliefs around this complex disruptive technology (Huang and Quian 2021). By demonstrating how investigating consumers' perceptions at different development stages can effectively describe the interaction of consumers' trust, well-being and behavioral intentions regarding fully autonomous cars, we suggest that such *dynamic* approaches can generate more in-depth insights than the dominant *static* approaches, which focus on only one level of automation.

Second, we contribute to the literature on technology adoption by integrating the traditional UTAUT framework with the psychological Theory of Subjective Well-being (Diener 1999; Diener and Chan 2011) and the Theory of Trust in Technology (McKnight et al. 2011). While the well-established UTAUT framework helps us to identify the cognitive antecedents of adoption, the well-being and trust frameworks shed light on the psychological mechanisms behind adoption. As the main goal of technological innovation should be to improve consumers' quality of life and increase their comfort and safety, investigating consumers' subjective well-being is both urgent and effective for comprehending how this technology can effectively improve it (Bertrandias et al. 2021). In addition, we highlight the link between trust and well-being. In fact, investigating trust is critical, as both ''overtrust'' and ''undertrust'' can be problematic for consumers' well-being by putting their life in danger and thus decreasing their perceived quality of life (König and Neumayr 2017; Lee and See 2004).

Third, we contribute to the literature on privacy concerns related to autonomous vehicles, empirically showing, for the first time, that consumers' experiencing AV functions plays a key role in addressing their concerns related to privacy (Meyer-Waarden and Cloared 2021). We suggest that the more consumers become accustomed to the benefits associated with a technology, the less they might be concerned about their lack of control over their personal information. In addition, we extend the existing literature by suggesting the importance of consumers' experiencing AV functions to decrease their privacy concerns, as such concerns might be detrimental to consumers' well-being, which, ultimately, is a strong driver of consumers' adoption (André et al. 2018; Du and Xie 2020; Munzel et al. 2018).

To conclude, the present study aims to overcome the limitations of online surveys by integrating them with field and simulator studies. In this regard, direct experience through field experimentations and product trials is a stronger and better predictor of consumers' behaviors than indirect experiences and surveys (Kempf 1999; Smith 1993).

7. Methodological Contributions

This study's methodological contributions include its innovative mixed method design and the advanced research tools implemented. In this regard, by integrating field and simulator studies, we were able to investigate how consumers' responses evolve when they experience increased levels of automation. To the best of our knowledge, this is the first time that such an approach has been implemented to investigate research questions concerning consumers' intention to use autonomous vehicles. We suggest that this dynamic approach can generate more in-depth insights when studying consumer behaviors related to new technologies. In fact, it offers an opportunity to analyze how consumers shape their perceptions about technologies before and after using them. Thus, by implementing a real environment where participants could directly experience a disruptive technology, we overcome the limitations of static and declarative surveys by obtaining a real understanding of users' behaviors when using AV technology (Kempf 1999; Smith 1993). In addition, simulator studies are useful when investigating a technology that is still not ready for its market, as they allow researchers to reproduce realistic environments.

8. Managerial Implications

The present study also offers managerial insights for practitioners. In particular, we highlight the importance of trial and experience with level 2 and level 5 automation to increase consumers' trusting beliefs toward fully autonomous cars and their behavioral intention to use. In particular, greater experience with automation levels can be useful to increase the effect of consumers' perceived functionality and reliability on their intention to use a fully autonomous car. The more consumers experience increasing levels of automation, the more their confidence in autonomous cars' 'abilities to drive effectively and properly' increases (McKnight 2011). In addition, the level of ambiguity around autonomous technology and algorithms, which makes them appear unpredictable and untrustworthy to consumers in many scenarios, can be overcome through more experience with functions with higher levels of autonomy. On the one hand, the utilitarian benefit related to consumers' performance expectancy is an important driver of adoption; on the other hand, when consumers experience higher functions, their performance expectancy's key role in affecting consumers' adoption does not increase. In this regard, we suggest that users might become accustomed to AV functions and their performances. In this case, managers should focus on other adoption factors, such as highlighting the larger role of the trusting beliefs of the reliability and functionality of the functions. In addition, we suggest that consumers' perceived well-being is an important driver of adoption, which should be highlighted. However, our results show that its effect on consumers' behavioral intention to use does not increase after they experience higher levels of automation. How fully autonomous functions might increase consumers' well-being might still be unclear in consumers' minds. For this reason, we suggest that managers should clarify how adopting higher levels of automation could benefit consumers in terms of their increased quality of life and well-being.

9. Limitations and Future Research Directions

Our study presents five main limitations that open the way to future research. First, we conducted the study in Germany, thus focusing the context of our analysis on a specific country. While Germany and the Stuttgart area are known for technology advancement/readiness (as Mercedes, Bosch and Porsche are based there) and one can consider that the studies and samples are representative of potential AV drivers for consumers, further research should replicate our study in different countries to enrich the literature on autonomous driving. In this regard, futher studies could adopt a cross-cultural approach, highlighting the cultural differences in affecting adoption (Edelmann et al. 2021; Rhim et al. 2020). For example, research should be conducted in countries with extended landscapes such as the US, or in emerging countries, such as China. The second limitation concerns the driving simulator. In fact, despite the numerous advantages of using a driving simulator, particularly the controllability, reproducibility, and standardization of scenarios and the possibility to test a technology that is not yet ready for its market, there are also some inconveniences, particularly the risk of limited physical and perceptual fidelity with the real context (De Winter et al. 2012). Although we tested the realism and credibility of the simulator, further empirical research should replicate our results with an actual fully autonomous level-5 car. Third, we do not account for the psychological traits of drivers, such as their degree of innovativeness or their driving styles, which could affect the way users perceive autonomous driving (Huang and Qian 2021). To overcome this issue, we suggest that future research should investigate these boundary conditions, particularly focusing on drivers' characteristics, such as innovativeness, driving style and attitude toward AV technology. In addition to the drivers' characteristics, we suggest that car characteristics should also be further investigated. For instance, the effect of brand extensions and brand preferences on consumers' autonomous vehicle acceptance should be taken into account (Eggers and Eggers, 2021). Moreover, as autonomous cars will probably include voice assistants, the effect of anthropomorphizing a car on consumers' trust and behavioral intentions might also be further investigated (Aggarwal and McGill 2007). In this regard, it is important to comprehend the way information related to the underlying decision-making process of the algorithms should be conveyed to a driver during driving tasks. Fourth, we do not account for situational factors, such as situation complexity, difficult driving conditions or potential technological failures, which could be further investigated. Finally, as we mainly investigate consumers' perception toward autonomous vehicles from a cognitive perspective, further studies should also investigate the emotional components of consumers' trust, well-being and acceptance.

To conclude, we call for more research that adopts a "development sensitive" design for other innovation application contexts, taking into account the different development stages and automation levels of new AI technology and the way consumers' perceptions gradually evolve.

10. Towards the Next Chapter: AI Ethics

In the previous chapters, we have focused on two practical applications of AI, chatbots and autonomous cars, and the way consumers are interacting with and using them. Both studies suggest that these technologies might have negative consequences for consumers well-being: in the case of chatbots consumers might experience higher negative emotions which, according to previous research, might decrease consumers' subjective well-being (Diener 1984); in the case of autonomous vehicles the lack of control over the personal information and privacy issues can decrease the perceived well-being. The fact that autonomous technologies might have consequences for humans in term of perceived life quality and life satisfaction has raised many questions concerning the ethics of implementing such innovations. In fact, the concept of well-being is grounded in the field of ethics (Sirgy and Lee 2008). Besides well-being and privacy issues, institutions and researchers have also highlighted other concerns that might raise questions about the ethics of implementing AI technologies, such as autonomy (André et al. 2018), safety and moral decision-making (Bonnefon et al. 2016), transparency (Hermann 2021; Murtarelli et al. 2021), biases and discrimination (Bostrom and Yudkowsky 2011; Du and Xie 2020; Murtarelli et al. 2021). If on the one hand the experts of the field have pointed out their worries around the technology, looking for answers and solutions; on the other hand, there is still a lack of comprehension of consumers' ethical concerns surrounding AI applications. Understanding their concerns, however, is important as they might affect the way individuals trust, accept and adopt the technology. In this context, by adopting an explorative approach, chapter 4 aims to give voice to consumers, investigating their ethical concerns around two of the main discussed and controversial AI applications: chatbots and autonomous vehicles.

:::

Introduction

PART I
Defining AI in Marketing

Chapter 1. Artificial Intelligence in Marketing Research: Scientometric, TCCM Review and a Research Agenda

PART II
Practical AI Applications

Chapter 2. Rage Against the Machine: Investigating Consumers Negative Emotions, Attributions of Responsibility and Coping Strategies in AI-Based Service Failures

Chapter 3. Now, Take your Hands from the Steering Wheel! How Trust, Well-Being and Privacy Concerns Influence Intention to Use Semi- and Fully Autonomous Cars

PART III
On the Ethics of AI

Chapter 4. Consumers' Perspectives on AI Ethics and Trust: an Explorative Investigation of Ethical Concerns Towards Autonomous Cars and Chatbots

Overall Theoretical, Methodological, Managerial Contributions, Research Limits and Future Research Directions

PART III

ON THE ETHICS OF AI

CHAPTER 4

CONSUMERS' PERSPECTIVES ON AI ETHICS AND TRUST: AN EXPLORATIVE INVESTIGATION OF ETHICAL CONCERNS TOWARDS AUTONOMOUS CARS AND CHATBOTS

1. Introduction

If on the one hand the development of Artificial Intelligence (AI) is often portrayed in terms of human progress and advancement, on the other hand there is a growing discussion over the downsides and risks associated to AI (Stahl et al. 2021). In this context, despite the fast and relentless development of AI, consumers seem to held many paradoxical feelings concerning intelligent technologies (Du and Xie 2020). The debate surrounding the ethics of intelligent products has already widely interested the academic community in various field, such as psychology (Bonnefon et al. 2016), philosophy and computer engineering (Etzioni and Etzioni 2017). Also the marketing literature has started to investigate the ethics surrounding AI, however often focusing the debate mainly on specific concepts such as privacy and data governance (Walker 2016). In addition, since the emerging marketing literature on AI ethics often adopt a conceptual approach to the problem (Letheren et al. 2020; Puntoni et al. 2021; Walker 2016), there is still the need to empirically investigate from a consumer perspective ethical concerns related to the implementation of disruptive AI technologies (Du and Xie 2020). We suggest that investigating consumers' ethical concerns towards AI product can be fundamental as they may affect consumer trust and the intention to use the technology. In this regard, the relationship between trust and ethics has been widely discussed in the literature, suggesting that when people develop trusting relationships, they evaluate the capacity of the other party for moral and actual self-commitment, in concordance with the person's ethical values (Argandoña 1999). Consistently, consumer trust in AI enabled products may depend, to a large extent, on how their key ethical concerns are addressed (Du and Xie 2020). In turn, widespread adoption of AI-enabled products depends on consumer trust in these products. Thus, if an AI product is negatively perceived because of its potential negative ethical implications, such as AI biases or privacy issues, consumers might be hesitant to use them. In this context, this paper intends to investigate ethical concerns surrounding AI by adopting a consumer perspective. Considering the wide spectrum of AI technologies, we try to better grasps how different AI-enabled products can raise different consumers' ethical concerns, focusing on two intelligent products: autonomous cars and chatbots. We select these two different units of analysis for three reasons: 1) if on the one hand they both contain a component of AI (Hengstler et al. 2016); on the other hand, they differ on the type of AI technique used and on their level of intelligence (Du and Xie 2020); 2) both technologies supplement or drive human decision making, but in very different contexts (Hengstler et al. 2016); 3) both of the applications requires user involvement (Hengstler et al. 2016), but the nature and the level of interactivity differs (Du and Xie 2020).

To investigate consumers' ethical concerns and their effect on trust, we employ a mixed methods research methodology. First, we use topic modeling to get insights about ethical concerns towards autonomous cars (Study 1) and chatbots (Study 2). Second, we implement structural equation modeling to predict the effect of ethical concerns on trust and intention to use the intelligent products. We show that if on the one hand data privacy is a shared concern between autonomous cars and chatbots, on the other hand ethical issues differ according to the product (Du and Xie 2020; Murtarelli et al. 2021). When talking about chatbots, consumers are concerned about human replacement, the lack of adaptability and they show ambivalent feelings towards the machine's emotional design. When considering autonomous cars, ethical design, transparency, road safety and accessibility emerge as main topics. We find an opposite perception of adaptability versus standardisation of algorithms in chatbots and autonomous cars: to increase trust, chatbots, perceived as unethical because unable to truly understand individual needs following predetermined rules, should guarantee adapted interactions; autonomous cars, perceived as unethical if their algorithms are not standardized, should follow common rules. We provide both theoretical contribution and managerial implications, offering insight to managers who want to increase trust and intention to use the technology by addressing customers' ethical concerns according to different products' characteristics.

Through this explorative study, we aim to answer a research gap in the consumer behaviors literature surrounding AI ethics, making one of the first empirical contributions around the topic.

2. Literature Review

2.1. Ethical Approaches to AI

According to Stahl et al. (2021) the goal and the role of ethical theories is to answer the question of why a particular action can be seen as good or bad or which processes would allow answering such a question. There are three main classical ethical theories that have tried to find an answer to the many ethical questions concerning what is good and bad. According to virtue ethics, ethics depends on individual character, on the way one develops good qualities or "virtues" such as honesty and on the ability to apply them (Hursthouse 1999). Thus, the ethical action is based on the character of the individual undertaking it and his/her internal principles (Stahl et al. 2021). By applying virtue-based ethical theories to artificial intelligence, researchers try to define the human virtues necessary to ensure the ethical design of AI and the respective values and virtues that needs to be embedded in the technology (Letheren et al. 2020). Ethical issues have been also analyzed through the lens of deontology which focuses on the agent's duty (Kant 1788). In particular, deontology conceives ethics in terms of laws or rules: individual actions are ethical if they conform to (or do not violate) the moral law. Duty-based theories focus on which action is right. In the case of AI technology, duty-based theories try to comprehend the different perspectives of what is "right" when it comes to the way AI should functions within society (Letheren et al. 2020). Teleology and utilitarianism, instead, rather look at the consequences and outcomes of actions to determine their ethical status (Mill 1861). Thus, utilitarianism basic principle is commonly formulated as "the greatest good for the greatest possible number" (Goldsmith and Burton 2017). When applying utilitarianism, researchers try to understand the consequences of the introduction of AI in society at the micro-level, meso-level and macro-level (Letheren et al. 2020).

In addition to the classical ethical theories, researchers have recently formulated new theories directly applied to technologies, such as computer ethics (Bynum and Rogerson 2003) and information ethics (Capurro 2006). According to Stahl et al. (2021) the current discourse around ethical issues of AI tend to put some distances from the classical philosophical ethical theories, rather adopting a more practical approach to define mid-level principles. Principles are at a middle level between fundamental classical theory and particular rules which are more restricted in scope (Coughlin 2008). According to Beauchamp (2010, p.7) "mid-level principles are not about what should be the goals of action but are rather about how any goal should be pursued". When defining good mid-level principles, experts discuss and agree upon useful moral guidelines in a particular field. Thus, the definition of ethical principles is a key aspect of the debate surrounding AI ethics (Stahl et al. 2021). Regulators, in fact, have tried to define and suggest ethical principles and ethical guidelines for AI (Jobin et al. 2019). For instance, the European Commission has published in 2019 the "Ethical guidelines for trustworthy AI", emphasizing a set of seven key ethical requirements that AI systems should meet in order to be deemed trustworthy: human agency and oversight, technical robustness and safety, privacy and data governance, transparency, non-discrimination and fairness, societal and environmental well-being, accountability (European Commission 2019).

2.2. Ethical Issues at the Individual and Societal Level

Besides the ethical principles which should guide AI and technology, many academics have started to investigate the ethical implications and potential consequences of implementing AI technologies both at the individual-level, at the organizational-level and at the society-level (Du and Xie 2020; Gaggioli et al. 2019; Riva et al. 2012; Verbeek 2015). At the individual-level, researchers have increasingly acknowledged that technologies embed ethical values, having a profound impact on the way individuals make decisions and behave (Du and Xie 2020; Verbeek 2015). According to Verbeek's Moral Mediation Theory of Technology (2015) individuals' moral perceptions and decisions are increasingly mediated by technology, due to the fact that human beings and technological artefact have become closely connected in daily life. Stahl and colleagues (2021) suggest that ethical issues related to AI are largely context-dependent. They categorize ethical issues into three broad streams: (1) issues directly related to machine learning, which rather address ethical concerns at the technological and individual level; (2) broader social and political issues arising in modern digitally enabled societies and finally (3) metaphysical questions.

The first stream refers to the opacity and transparency of machine-learning techniques which are often difficult to interpret. In this regard, the authors suggest as even experts with relevant equipment might find difficult to determine why and how inputs are transformed into outputs (Stahl et al. 2021). The lack of transparency behind AI algorithms might cause ethical issues related to bias and discriminations, as programmer might not be able to control the information processed and the consequent algorithmic decision making (Stahl et al. 2021). In this regard, Loureiro et al. (2020) suggest that despite studies conducted to bring transparency to the complex learning procedures that are inherent to AI, more research is needed to translate AI language to human language. In addition to the transparency of algorithms, the machine learning systems often access big amounts of data for training and validation purposes, thus causing problem related to privacy, data protection, security and integrity of the system (Stalh et al. 2021). In this regard, also Du and Xie (2020) suggest that between the main issues related to AI at the individual level there are cybersecurity and privacy. With the increasing implementations of recommendation systems and autonomous technologies, also the autonomy of choice has been highlighted as a critical issue (André et al. 2018). In this regard, as Saura et al. (2021) suggest, artificial intelligence training algorithms can lead the users to make decisions without being aware of making them. All these issues might be problematic at the individual level, having potential consequences for consumers and citizens who increasingly rely on AI for their daily life activities (Du and Xie 2020; Stahl et al. 2021).

The second stream refers to the way societies use technologies and the consequences they might have at the societal and political level. Economic consequences, human replacement and unemployment, inequality, military use, power asymmetry, responsibility and sustainability issues all fall into this stream (Stahl et al. 2021). In this regard, according to Loureiro and collegues (2020), current laws governing citizens should be reviewed and extended to AI systems to regulate, for instance, the liability of AI technologies in case of accidents causing physical or psychological damage to a human entity.

Finally, the third stream refers to philosophical and metaphysical questions about the nature and the future of AI. In this regard, there is a growing concern that as AI becomes smarter and more autonomous, people would lose control over its advancement and evolution (Loureiro et al. 2020). A new society, based on AI agents and hybrid humans, could bring new societal and environmental challenges (Loureiro et al. 2020). Thus, the topics related to general and strong AI, transhumanism, singularity and change of the human nature fall in the third research stream (Stahl et al. 2021).

2.3. Ethical Issues According to the Products Characteristics

Despite the need of having a general framework concerning the ethics of AI, researchers have also started to highlight the importance of considering the way specific product characteristics affect ethical concerns involving AI. In fact, not all AI-products are the same, using different AI techniques, having different goals, applications and potentially engendering different ethical consequences both at the individual level and societal level. In this regard, Du and Xie (2020) highlight three important characteristics of intelligent products: multi-functionality, level of interactivity and stage of AI. Each of these characteristics raises different ethical challenges. Multi-functionality refers to the range of tasks that a product can perform. High level of multi-functionality may be related to autonomy issues, while low level of multi- functionality may increase biases of the machine (Du and Xie 2020). Interactivity refers to the nature of the interaction with the machine including the type of interface and modality. The interactivity is strong when the interaction format is synchronous, modality-rich and anthropomorphic. For instance, AI-based chatbots or digital assistants such Alexa have higher levels of interactivity, communicating in a human-like way (Köhler et al. 2011). AI-enabled products that are high on interactivity are more likely to face ethical challenges related to privacy (Du and Xie 2020). The third dimension is related to the level and type of intelligence. In this regard, product differs on their level of complexity and techniques used. For instance, autonomous vehicles, which are able to sense the world with such techniques as laser, radar, lidar, Global Positioning System (GPS) and computer vision, are developed across seven levels of automation, from the less complex (level 1) to the most complex and developed level (level 7). Conversational agents, which use instead different AI techniques than autonomous cars, mainly natural language processing, are also distinguished according to their level and type of intelligence, which can be mechanical, analytical, intuitive, and empathetic (Huang and Rust 2018). If on the one hand the mechanical intelligence is at the lowest level, as the machine follows only predetermined rules, on the other hand, empathetic intelligence is the highest and most complex, as the machine would be able to understand consumers' emotion and react accordingly (Huang and Rust 2018). As suggested by Du and Xie (2020), considering the level and type of intelligence is fundamental, as the higher is the level of intelligence of the machine, the higher and more complex are the ethical concerns surrounding the technology.

2.4. Trust and Ethics

Investigating ethical concerns is fundamental to comprehend also the way individuals develop trust towards new disruptive products which might be perceived as risky. In fact, a wide stream of research has considered ethical perceptions as the essence of trust (McKnight et al. 2002). As Mayer et al. (1995) suggest, a trustee who is perceived to behave ethically is considered as a desirable exchange partner. In particular, the cognitive aspects of trust involves beliefs that the trusted party will behave ethically, dependably and will carry out expected commitments under conditions of vulnerability and dependence (Gefen et al. 2003). Consistently, according to Argandoña (1999), besides the perceived competence, loyalty, good will, fairness and integrity of the trustee, trust is also based on the perceived capacity of the other party for moral and actual self-commitment, in concordance with the person's moral values. As in interpersonal relationships, also in human technology interactions there is a series of technical, psychological and, especially ethical conditions which make trust possible (Argandoña 1999). In fact, according to Du and Xie (2020), consumer trust in AI-enabled products depends, to a large extent, on their key ethical concerns, such as AI biases, cybersecurity and privacy, and on the way they are addressed. In turn, the adoption of AI-enabled products depends on consumer trust in these products (Gefen et al. 2003). In fact, because of the perceived risk associated to AI, as well as the complexity and non-determinism of AI actions, trust is especially important in human-AI relationship (Glikson and Woolley 2020).

According to Glikson and Wooley (2020), when investigating trust towards a technology is important to consider the task characteristics and immediacy behaviors of the technological product. A task characteristic refers to the task that the technology can perform, such as dealing with largely technical versus interpersonal judgments. Technologies are believed to be more efficient in some tasks than in others. Therefore, task characteristics can be an important for cognitive trust in AI, which is based on consumers' beliefs that the technology is going to perform in a reliable and dependent way (Glikson and Woolley 2020). As the range of tasks that AI can perform keeps growing, the role of task characteristics in developing cognitive trust becomes more complex and less stable. AI-enabled products, in fact, are increasingly able to execute not only traditional technology-related tasks, but also more complex tasks that generally require human intelligence. This could raise ethical concerns at the individual and societal level, such as the role of the machine in replacing humans or making decision in critical situations, thus perceiving the technology as less dependable and reliable.

Immediacy behaviors refer instead to the degree of interactivity of the machine (Du and Xie 2020; Glikson and Wolley 2020). The higher is the intelligence of the machine, the more it is able to interact with the environment and be responsive to users. Immediacy behaviors include socially-oriented gestures intended to increase interpersonal closeness, such as proactivity, active listening, and responsiveness (Glikson and Woolley 2020). These behaviors, which are perceived as signs of machine intelligence, can influence trust by raising the expectations of high-quality performance. Through immediacy behaviors and high levels of interactivity, programmers specifically target human emotions by manipulating features of AI, for instance increasing the anthropomorphism of the machine. Anthropomorphism refers to the perception of technology or an object as having human qualities, such as feelings (Epley et al. 2018). Making a bot to look or act like a human is known to affect users' emotional reactions toward the technology. However, the effect is not always positive, and may also result in negative emotions, such as a sense of eeriness and fear. Also in this case, the features and characteristics of the AI-product might raise different ethical concerns about the nature of the technology and the relationship with the AI-product, which could differently affect the development of trust. Thus, in order to better grasps how different ethical concerns raise and how trust towards different AI products is developed, this study investigates two different units of analysis.

3. Methodology

3.1. Selection of the Units of Analysis

Autonomous vehicles and chatbots are two examples of new intelligent products which have widely raised ethical concerns of researchers and the community in general (Bonnefon et al. 2016; Hengstler et al. 2016; Murtarelli et al. 2021). Despite fully autonomous cars are still not available to the mass market, consumers can already buy semi-autonomous cars which are able to execute specific tasks such as automatic braking, acceleration and steering (Hengstler et al. 2016). Chatbots, instead, represent a widely implemented technological evolution of the traditional service (Chung et al. 2018; Huang and Rust 2018; Luo et al. 2019). We draw from Hengstler et al. (2016) and Du and Xie (2020) for the selection of these two intelligent applications as units of analysis according to three criteria. First, if on the one hand they both contain a component of AI (Hengstler et al. 2016), on the other hand they differ on the type of AI technique used and their level of intelligence (Du and Xie 2020). Autonomous vehicles mainly use computer vision to detect objects in the surrounding environment, and deep learning to elaborate information. They are considered as one of the most complex and promising AI technologies. Chatbots are software-based services which mainly use machine learning and natural language processing (Shawar and Atwell 2005). They are often at a lower level of mechanical and analytical intelligence (Huang and Rust 2018). Second, both technologies tend to substitute or orient human decision making (Hengstler et al. 2016), but they are being used in different contexts, presenting different task characteristics and functionalities (Glikson and Woolley 2020). In this regard, driverless cars are learning machines which are able to change the ways they conduct themselves without -or almost- human intervention. By being able to make decisions in critical situations, autonomous cars may substitute human decision making. Also chatbots are learning machines. Nevertheless, their tasks mainly involve the ability to engage in conversations, rather orienting human decision making (Du and Xie 2020; Luo et al. 2019; Murtarelli et al. 2021). Third, both applications require user involvement (Hengstler et al. 2016), but the nature and the level of interactivity, in particular the modality, the interface and their immediacy behaviors differ (Du and Xie 2020; Glikson and Woolley 2020). In fact, chatbots are different from other AI-enabled technologies due to their ability to simulate human-like interactions to such an extent that customers may well not realize that they are talking to a chatbot rather than human, thus raising ethical concerns about the nature of the chatbot and the authenticity of the interaction (Murtarelli et al. 2021).

3.2. Procedure

In order to investigate consumers' ethical concerns towards autonomous cars and chatbots we conduct two studies. By adopting a mixed method approach, each study is divided in two phases.

3.2.1. Phase 1

We conduct two studies, one related to the ethical concerns towards autonomous cars (Study 1) and one related to the ethical concerns towards chatbots (Study 2). In Study 1 we administer to a sample of 138 German participants a written open-ended question asking them to write about what they think of fully autonomous cars from an ethical point of view. The 37% of the sample are women and the 63% are men. The age and gender distributions are shown in Table 50.

In study 2 we administer a written open-ended question to a sample of 161 French participants asking them to write about what they think of chatbots from an ethical point of view. The 56% of participants are women and the 44% of the participants are men. Table 51 shows the age and gender distribution of Study 2.

Table 50 Age and gender distribution of Study 1

		Gender		**Total**
		Women	**Men**	
Age	18-29	14	35	49
	30-39	9	11	20
	40-49	9	10	19
	50-59	16	16	32
	60-69	3	7	10
	>70	0	8	8
Total		**51**	**87**	**138**

Table 51 Age and gender distribution of Study 2

		GENDER		**Total**
		Women	**Men**	
Age	18-29	10	10	20
	30-39	16	9	25
	40-49	18	12	30
	50-59	13	15	28
	60-69	13	9	22
	>70	20	16	36
Total		**90**	**71**	**161**

Before the open-ended question, we also measure on a 7-point Likert scale trust towards autonomous cars (α=.872) and chatbots (α=.871) adapting the scale of Gefen (2002) (I am quite certain about what to expect from autonomous cars/chatbots; I believe that autonomous cars/chatbots are trustworthy; I believe that autonomous cars/chatbots are predictable) and intention to use autonomous cars (α=.916) and chatbots (α=.961) adapting the scale of Kulviwat et al. (2007) (Assuming that I have access to autonomous cars/ chatbots in the future, the probability I would use them is: unlikely/likely; impossible/possible). We employ topic modeling using R 3.4.0 software to analyse the open-ended questions. We use this technique to explore important themes from textual data inspired from earlier research where NLP and text mining techniques are used to extract important information from the text (Ray et al. 2021; Villarroel Ordenes and Zhang 2019). In particular, topic modeling is a bottom-up approach where researchers firstly examine patterns in text, and then propose interpretations of results (Wang and Humphreys 2018). According to Berger et al. (2019) this approach is particularly useful when the objective is insight generation rather than prediction. First, we pre-process the text according to the steps of Berger et al. (2019). In particular, we break text into units of words (tokenization), we remove non-meaningful text and non-textual information (cleaning), we remove stop words such as articles and prepositions (removing stop words), we correct spelling mistakes (spelling) and we reduce words into their common stem of lemma (stemming and lemmatization). Next, we use Latent Dirichlet Allocation (LDA) to identify the general topics, described as a combination of words, recognizing patterns within the data (Wang and Humphreys 2018). LDA represents topics by word probabilities. We draw from Wang et al. (2015) defining the number of topics and the label of each topic according to the semantic coherence and word intrusions. The words with highest probabilities in each topic helps researchers to define and label the topics (Jelodar et al. 2019). We also label and define the topics according to the comments associated to each of them.

3.2.2. Phase 2

Based on the topics generated, the conceptual model is developed and tested quantitatively using Structural Equation Modeling (SEM). In particular, the topics are treated as observed variables of the path-model. The generated probabilities of each topic are standardised. Thus, we conduct a structural equation analysis to assess the effect of topic probabilities on trust towards autonomous cars (Study 1) and chatbots (Study 2), and the effect of trust on intention to use autonomous cars (Study 1) and chatbots (Study 2). SEM analysis is also performed using R 3.4.0 platform.

4. Results

4.1. Study 1: Ethical Concerns Towards Autonomous Cars

4.1.1. Phase 1

We run the topic modeling analysis identifying four main topics representing consumers' ethical concerns towards autonomous cars. Table 52 shows the 15 highest-ranked keywords for each topic. The right column shows four examples of open-ended comments that have a high proportion of the topic. Based on the keywords and on the comments, we define a label for each topic. Thus, we name the four topics as transparency, road safety, accessibility, ethical design.

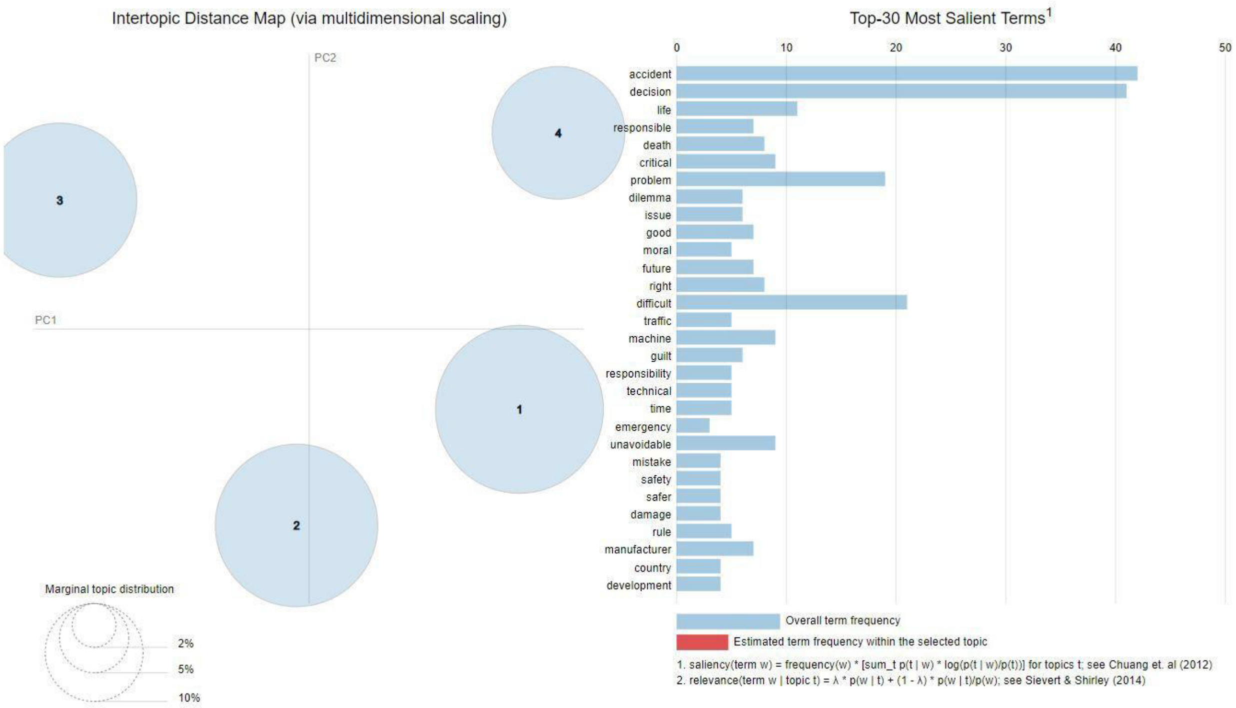
Table 52 Topics of Study 1

Topic label	Keywords	Representative comments
1.Transparency	Decision, right, guilt, rule, machine, difficult, manufacturer, data, decide, fault, positive, questionable, protection, society, algorithm.	"Clear rules about the algorithm should be in place". "I think that society must first answer the question of how a vehicle should decide: this difficult decision should not be left to companies". "I see data protection as a problem". "As we have to disclose a lot of personal data, I do not think much of it".

2.Road safety	Future, mistake, safety, safer, damage, accident, aware, conflict, dangerous, idea, safe, style, problem, cost, environment.	"If autonomous cars improve road safety, everyone should be aware of the need to use this. Fear, however, that some drivers may become careless and lose concentration. Keyword: The driver must always be ready to react"; "If autonomous driving can bring the number of accidents to zero, which I expect, this is a very good development". "Autonomous vehicles will certainly react better in dangerous situations than humans". "I assume that autonomous cars will only come onto the road when they are sufficiently safe - i.e. significantly safer than the average driver. Due to the expected restrained driving style, I expect significantly fewer accidents overall"
3.Accessibility	Responsible, dilemma, issue, moral, critical, emergency, age, behavior, disabilities, group, principle, problematic, role, self, accessible.	"I think that autonomous cars can help to give more people (e.g. with various disabilities) access to individual mobility and thus a more self-determined life". "Positive, help for groups of people who are no longer so mobile. E.g. pensioners, disabled people". "It is necessary to make them accessible to the people and to make them familiar with the new technologies". "Access probably only possible in rich industrialised countries for the foreseeable future. What about Africa, South America, India, etc.?"
4.Ethical design	Life, death, good, traffic, responsibility, technical, time, accident, country, development, social, software, system, injury, company.	"Since ethics always has to do with moral principles and this morality is shaped by the individual or a society (different societies/countries have different moral concepts) it is very difficult to introduce this morality firmly and clearly into a machine". "There would have to be exact legal regulations. It could lead to conflicts in politics and population. Autonomous vehicles must be programmed to give control to humans in unclear situations to avoid wrong machine decisions". "Morally it could be difficult if an accident occurs and who is finally responsible". "Can the software developer, or the manufacturer, be held responsible for wrong decisions of the vehicle?"

We also use multidimensional scaling to represent the intertopic distances (Figure 27). The intertopic distance map plots the topics on a multidimensional scale to present how similar each topic is to the others. The distances between the centres of the circles demonstrate that topics are different between each other, not overlapping. Topics that are closer together have more words in common. In particular, topic 1 (transparency) and topic 2 (road safety) are closer than the other topics. The frequency is presented via the size of each circle: the area of the topic circles is proportional to the number of words that belong to each topic. The right panel in the LDAvis dashboard lists the Top-30 most relevant terms in the data set in terms of overall term frequency, such as accident, decision, difficult, problem life, unavoidable, critical, dearth, responsible etc.

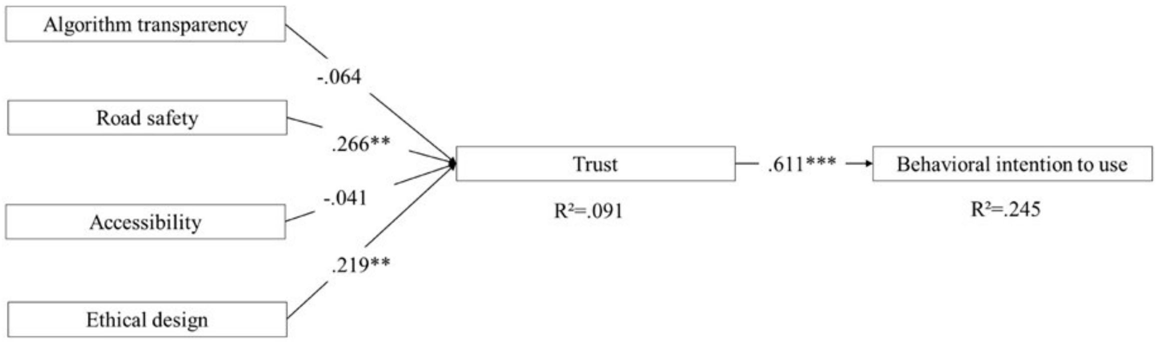
Figure 27 Intertopic distance map of Study 1



4.1.2. Phase 2

Next, we conduct a SEM in R to test the effect of the topics on trust and the effect of trust on the behavioral intention to use autonomous cars (Figure 28). Results show that transparency does not have a significant effect on trust ($b=-.064$, $p>.05$); road safety has a positive significant effect on trust towards autonomous car ($b=.266$; $p<.001$); accessibility does not have a significant effect on trust ($b=-.041$, $p>.05$); ethical design has a positive significant effect on trust towards autonomous car (*b*=.219*; p*<.01). Trust has a significant effect on intention to use autonomous cars (*b*=.611*; p*<.001).

Figure 28 Effect of ethical concerns on trust and intention to use autonomous cars



***p<.001; **p<.01

4.2. Ethical Concerns Towards Chatbots

4.2.1. Phase 1

Concerning Study 2, we identify four main topics describing consumers' ethical concerns towards chatbots. We name the topic according to the respective keywords and the representative comments (Table 53). In particular, we label the four topics as human replacement, emotional design, privacy concerns, and adaptability. We report the 15 most important keywords.

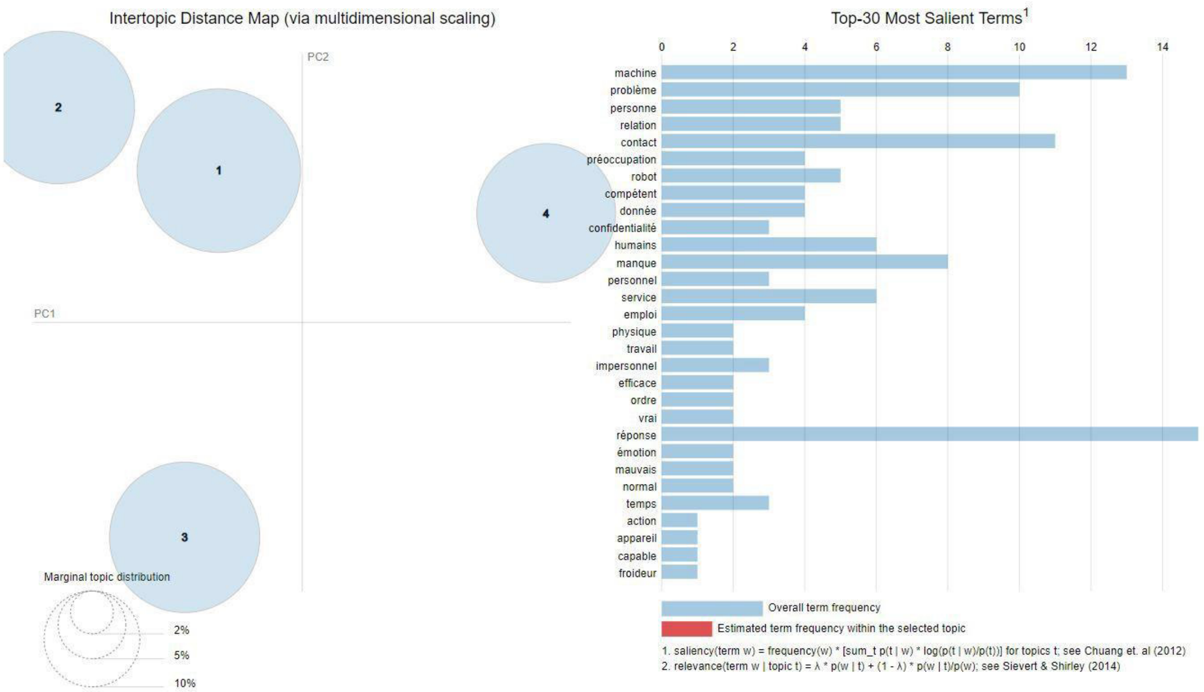
Table 53 Topics of Study 2

Label	Keywords	Representative comments
1.Human replacement	Person, physical, work, action, device, capable, cold, plan, robots, automatic, client, concrete, trust, consequence, creepy.	"My ethical concern is the person who has lost his or her job to be replaced by a machine". "On an ethical level I think that chatbots take the work of human beings". "It's only an impersonal machine". "There is no soul in the relationship with the client".
2.Emotional design	Competent, data, personal, emotion, bad, normal, good,	"I am concerned about the emotions and the tone of voice

	capability, domain, efficiency, being, humanity, incapable, intelligence, computer, predefined.	of the machine". "They can only answer simple questions: no humanity and no intelligence". "They do not understand emotions". "It is necessary to be pragmatic and not in an emotional state because that is not managed very well by the chatbots today". "A chatbot is a tool programmed by humans and unable to leave a predefined framework. And it's silly to put a human on a chatbot that has no feelings or emotions”.
3.Privacy concerns	Preoccupation, privacy, ease, difficult, exchange, reliable, tool, reduction, outcomes, call, after sales, advice, concept, conduct.	"I am concerned about privacy and data protection". "The confidentiality of my information". "They are not reliable". "I do not feel not comfortable when interacting with chatbot".
4.Adaptability	Relation, efficiency, order, authentic, practical, relationship, usage, adaptation, case, agent, approximate, artificial, aspect, automatization, capability	"They don't really answer the questions asked, I have to go through a real contact to get the expected answers". "Lack of adaptability". "I can't have authentic conversations with them". "Chatbot repeat ready-made phrases and do not solve problems, thus wasting time and energy".

We use again the multidimensional scaling to represent the intertopic distances (Figure 29). The distances between the centres of the circles demonstrate the topics are different between each other, not overlapping. However, topic 1 (human replacement) and topic 2 (emotional design) are closer that the other topics. The size of each circle reflects the significance of each topic. The bar chart identifies the 30 most salient terms in the data set, such as response, machine, contact, problem, lack, humans, relation, person etc.

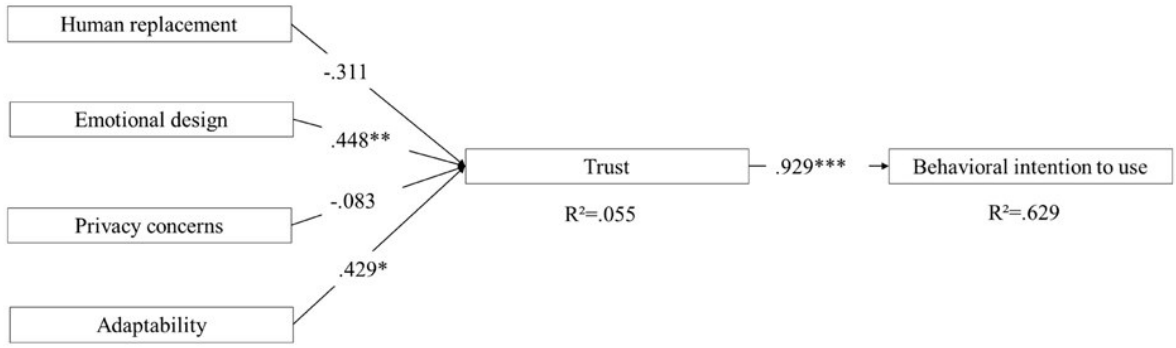
Figure 29 Intertopic distance map of Study 2



4.2.2. Phase 2

Next, we conduct a SEM to test the effect of the topics prevalence on trust and the effect of trust on the behavioral intention to use chatbots (Figure 30). Results show that human replacement does not have a significant effect on trust (b=-.311, p>.05); emotional design has a significant positive effect on trust (b=.448, p<.01); privacy concerns do not have a significant effect on trust (b=-.083, p>.05); adaptability has a significant positive effect on trust (b=.429, p<.05). Trust has a significant effect on intention to use chatbots (*b*=.929*;* *p*<.001).

Figure 30 The effect of ethical concerns on trust towards chatbots and intention to use



***p<.001; **p<.01; *p<.05

5. Discussion

5.1. Ethical Concerns Towards Autonomous Cars

By adopting a consumer perspective, we identify four main topics related to the ethical concerns towards autonomous cars: transparency, road safety, accessibility, and ethical design.

5.1.1. Transparency

Transparency reflects the level to which the underlying operating rules and inner logics of the technology is apparent to the users (Glikson and Woolley 2020). According to Glikson and Wolley (2020, p.13) “an important aspect of transparency includes different types of explanations regarding how AI works or why a specific decision was made being understandable to users, even when they have little technical knowledge”. Thus, transparency is especially needed for highly intelligent systems, such as autonomous vehicles, considering their level complexity and opacity of information processing (Felzmann et al. 2019). In this regard, the participants of the first study highlight the need to have transparent rules which clearly define the algorithmic decision making, for instance in critical driving situations where the machine might have to make important life-death decisions. Besides, participants seem to be concerned on the way their personal data are processed by the technology. In fact, higher capabilities require more consumer data, making privacy issues prominent (Du and Xie 2020). In this regard, data privacy is related to the dissemination and use of information (Martin and Murphy 2017). Complex technologies raise particular challenges not only because of their information processing nature and contexts of use but also because of the multitude of stakeholders potentially affected by the transparency requirements, such as companies and institutions (Glikson and Woolley 2020). In this context, transparency is a core principle in data protection. For instance, the European Union's General Data Protection Regulation (GDPR) includes transparency as a proactive requirement for information technologies that process personal data, demanding transparency by making data processing explicit to the user (Felzmann et al. 2019). Transparency helps users to understand how the algorithm is implemented and how data are collected and processed, facilitating an informed consent process that allows users to make meaningful decisions about the way they are going to use the technology.

5.1.2. Road Safety

The second topic concerns road safety. Participants show a positive attitude towards the potential ability of the car to prevent humans' mistakes, highlighting the fact that autonomous cars could be safer than the "average drivers", "older people" and "novice drivers". In this regard, institutions, companies and academic seems to agree that autonomous vehicles could spare many of the 1.25 million lives that are lost annually due to traffic collisions caused by human mistakes (Shariff et al. 2021). However, if on the one hand the participants of the study show positive attitudes towards autonomous driving thanks to its potential safety benefits; on the other hand, they are concerned about the potential backfires of autonomous cars. For instance, they mention that “drivers may become careless and lose concentration”; they might “lose their reaction times”, thus potentially causing other critical and dangerous situations. In addition, they highlight that the acceptable level of safety needs to be clearly defined. In this regard, participants of the study hope that “autonomous cars will only come onto the road when they are sufficiently safe, in particular significantly safer than the average driver”. Consistently, legislators are discussing the safety requirements necessary to make autonomous vehicles enter the market. For instance, the German autonomous vehicle ethics committee published recommendations in 2017 that connect the implementation of AVs to their ability to demonstrate that they are demonstrably safer than human drivers (Shariff et al. 2021). In reality, how much safer cars need to be before entering the market, is still an open question. According to Shariff et al. (2021) the level of safety required may be shaped by the psychology of both regulators and the consumer. The authors suggest that people require higher levels of safety when being driven by an AV than a human, having much more stringent and unrealistic safety thresholds related to AV. Consistently with their findings, participants of our study declared that they would use autonomous vehicles only if the “security is 100% guaranteed”. This unrealistic safety threshold might slow down the introduction of autonomous cars in the market. In fact, while perfecting AV technology, society might already lose the potential benefits of using autonomous cars already safer than the average human drivers (Sharif et al. 2021).

5.1.3. Accessibility

Accessibility has become a central concept in transportation research (Eppenberger and Richter 2021). Geurs and van Wee (2004, p. 128) define accessibility as “the extent to which land-use and transport systems enable (groups of) individuals to reach activities or destinations by means of a (combination of) transport mode(s)”. According to Lucas et al.

(2016), from an ethical perspective low levels of accessibility are inherently related to high levels of social exclusion. In order to reduce transport-related social exclusion, some transport policies are introducing new services and technologies (Lucas et al. 2016). For instance, autonomous vehicles represent a pathway that could increase accessibility to transportation and mobility of the senior and disabled individuals by decreasing human involvement during the driving task (Harper et al. 2016). Besides social exclusion, accessibility is also linked to broader concepts of quality of life, happiness and wellbeing (Lucas et al. 2016). In fact, many seniors and people with medical conditions often face challenges traveling freely and independently and must rely on family, friends, or others (Harper et al. 2016). However, as highlighted by the participants of the study, “autonomous cars can help to give more people (e.g. with various disabilities) access to individual mobility and thus a more self-determined life". If on the one hand participants highlight the bright side of autonomous vehicles in terms of higher access for some groups of individuals, on the other hand they also highlight the risks of inequalities due to lower accessibility for other groups. For instance, they state that one negative aspect of autonomous vehicles is that “they might not be available to all people due to the higher costs” and that “access to autonomous vehicles would probably only possible in rich industrialised countries” thus increasing inequalities with less developed countries such as Africa, South America and India. In this regard, there is the risk that autonomous cars will be offered at high cost, potentially leading to social exclusion of lower income groups (Thomopoulos and Givoni 2015). The risk of inequalities also lies in the way the algorithms are going to make decisions and being responsible for their choices. In particular, the prospect of recognising individual characteristics raises concerns about which features autonomous vehicles will recognise and what weight these should be accorded (Liu 2017). In this regard, participants state that “decisions should not be based on individual characteristics such as age, appearance or other individual characteristics”.

5.1.4. Ethical Design

As AI-enabled products are going to be able to make critical decisions in many situations, it is becoming increasingly important to integrate ethical values to drive machine behaviors (Etzioni and Etzioni 2017). For instance, in the context of autonomous cars, researchers and regulators have been discussing how the machine has to make important life-death decision in case of accidents (Awad et al. 2018; Bonnefon et al. 2016). In this regard, researchers have been trying to find answers to the well-known “trolley problem”. In particular, through a series of thought experiments involving ethical dilemmas of whether to sacrifice one person (which can differ in terms of socio-demographic characteristics) to save a larger number, researchers have tried to define the moral values that could define decision making in critical situations (Bonnefon et al. 2016). However, research shows that embedding ethical values in AI is complex as the moral standard that people expect from autonomous driving algorithms differs across groups and countries (Bonnefon et al. 2016). In this regard, the participants of our study highlight the urgency of having a standardized, international regulation that unanimously defines the way the machine makes moral decision in case of ethical dilemma. Thus, participants seem to prefer a deontological and a virtue-based approach, rather than a consequentialist one. In addition, the way the responsibility is attributed in case of accidents needs to be clarified by regulators (Du and Xie 2020; Hengstler et al. 2016). In line with Li et al. (2016), when examining how participants consider assigning moral and legal responsibility in case of accidents with autonomous vehicles, we identify two main targets of responsibility. First, responsibility for accident damage could be assigned to parties that produced the technology, in particular the car manufacturer and the software developer. Second, the responsibility could be given to the owner of the car. Clarifying how the car will make the decisions in case of ethical dilemma, and who will be held as responsible in case of car crashes is one of the fundamental step in reducing the uncertainty surrounding the implementation of the technology (Awad et al. 2018).

5.2. Ethical Concerns Towards Chatbot

Also, in Study 2 four main topics emerge highlighting consumers' ethical concerns towards chatbots. Participants revealed different ethical issues which are linked to the higher level of interactivity and the different tasks characteristics of the technology (Du and Xie 2020; Murtarelli et al. 2021). In particular, they indicate human replacement, the emotional design, privacy concerns and the need of adaptability as main ethical concerns.

5.2.1. Human Replacement

As AI become more complex and intelligent, human replacement by AI is increasingly raising individuals concerns. In particular, unemployment due to job replacement is one important discussed topic, which has also raised the attention of researchers and regulators (Du and Xie 2020; Huang and Rust 2018; Raisch and Krakowski 2021). Since jobs fulfil many individual needs, the potential disruptive impact of AI on employment might have strong ethical and societal implications, potentially decreasing consumers' well-being and sense of life satisfaction (Du and Xie 2020). In this regard, our participants declared to be worried about "the person who has lost his or her job to be replaced by a machine". In this context, companies have an ethical responsibility to protect the interests of their employees, engaging in initiatives that address the risk of unemployment due to AI (Du and Xie 2020). For instance, reskilling employee could be crucial to avoid unemployment (Du and Xie 2020). In addition, to really benefit from the technology companies should learn to augment employees with AI, rather that substituting them (Raisch and Krakowski 2021). According to Raisch and Krakowski (2021), balancing automation and augmentation could enable a virtuous cycle of selective deskilling and strategic requalification, improving both human and machine abilities. In fact, employees whose fundamental abilities are rendered obsolete by automation may be offered the chance to progressively develop higher-level skills that are in demand. In this regard, Huang and Rust (2018) suggest that if on the one hand analytical skills will become less important as AI takes over more analytical tasks; on the other hand the “softer” intuitive and empathetic skills will become even more important. Besides unemployment, however, human replacement by AI might also affect the way individual develop relationships. In this regard, participants stated that one of their main concerns is that "there is no soul in the relationship with the client" and that is “only an impersonal machine”. In this regard, human replacement by AI might foster dehumanization by depriving people of human contact, creating feeling of loneliness and frustration (Puntoni et al. 2021; Wirtz et al. 2018). Dehumanization is defined as “perceiving a person or group as lacking humanness” (Haslam and Loughnan 2014, p.401). Research has shown that very human-like but not human objects elicit an uncanny valley effect as they combine “human and nonhuman features” (Mori 1970). This might create a sense of creepiness engendering negative feelings of dehumanization. Consistently, participants defined chatbots as “inhuman and creepy”.

5.2.2. Emotional Design

Despite the developments in social robotics are making it possible to create emotional AI-powered service interactions (van Doorn et al. 2017), most of the bots implemented by companies are still at the mechanical and analytical level (Huang and Rust 2018). In this regard, they still lack the emotional intelligence necessary to understand consumers’ feelings and respond adequately. In fact, participants declare that one problem with this type of AI is that it “does not understand emotions". The lack of emotional understanding might results in consumers’ frustration decreasing their well-being (Diener 1984; Frow et al. 2019). However, participants seem to have ambivalent feelings: on the one hand they address the lack of humanity and coldness as an issue; on the other hand, they suggest a feeling of discomfort when chatbots show emotions and empathy. In fact, participants state that they might feel uncomfortable when a robot or computer tool reacts like a human with phrases such as "I'm sorry to hear that”. In addition, the lack of emotions is also linked to the pragmatic usage of chatbots which are often implemented to solve basic issues, suggesting that "it is necessary to be pragmatic and not in an emotional state because that is not managed very well". Despite many studies show the importance of humanizing the machine through the implementation of emotional reaction to increase trust, our results are in line with a growing number of researches suggesting that implementing emotions in machines could generate negative reactions such as discomfort (Mende et al. 2019). We suggest that, depending on the task characteristics, participants might positively perceive the trade-off between emotion and efficiency, preferring a competent, efficient chatbot, rather than an emotional one which could foster feelings of discomfort (Meyer-Waarden et al. 2020).

5.2.3. Privacy Concerns

Consumers are becoming increasingly concerned about privacy also in relation to conversational agents. As suggested by Du and Xie (2021) the higher is the level of interactivity of the machine and the immediacy behaviors, the more privacy issues become relevant. In fact, due to the data-centric nature of AI technologies and to the high level of interaction with the machine, the volume and variety of consumer data that are collected, utilized and transmitted is dramatically increasing, triggering new ethical challenges concerning data protection (Du and Xie 2020). Besides textual, visual, audio and verbal data, also other sensory data might be collected without consumer awareness and consent. In addition, the way companies are going to use consumers’ data can be not clear and fully transparent. Thus, consumers concern about the way their data are used are becoming a prominent issue that need to be addressed by firms and regulators. In this context, Thomaz et al. (2020) suggest that there are two types of consumers in relation to privacy: those who are willing to give permission to firms to track, record, use, and share information (e.g., purchase and site visit histories) in exchange of more personalized services, and those who instead deny access to such information. The decision of sharing information can be the results of a privacy-calculus assessment, where consumers weigh privacy concerns and related risks against the benefits of information disclosure, such as personalization, access to free services or financial compensation (Cloarec 2020; Dinev and Hart 2006; Thomaz et al. 2020). Besides increasing the perceived benefits, companies might try to also decrease the perceive risks of disclosing information. According to recent studies, anthropomorphising the technology can benefit the privacy calculus by diminishing perceived risks related to privacy. In fact, anthropomorphism might foster information disclosure by triggering "mindless" responses from people, to the extent that people apply social scripts used in human-to-human interaction to conversational agents (Nass and Moon 2000; Thomaz et al. 2020). In addition, anthropomorphising the machine might trigger norms of reciprocity and increase the trustworthiness of the machine by augmenting its perceived social presence (Epley et al. 2018, van Doorn et al. 2017). However, while anthropomorphism can generate positive results (Aggarwal and McGill 2007), too much of it can also lead to negative effects, such as discomfort (Thomaz et al. 2020). To alleviate consumers concerns, companies could adopt an ethical approach providing a transparent and easy-to-understand communication about their privacy policies. In addition, they could guarantee consumer more control over their personal data, the way they are collected, stored and used (Du and Xie 2020; Martin and Murphy 2017).

5.2.4. Adaptability

The last topic involves the lack of adaptability of conversational agents. In particular, chatbots are perceived as unethical because of their inability to truly understand individual needs and develop unique relationships, following standardized rules and not being able to "adapt" and to "get out of the paths they have in their memory". In this regard, adaptability in service settings refers to the ability of service employees to adjust their behaviors to the interpersonal demand of the service encounter in order to meet the needs of customers (Gwinner et al. 2005; Hartline and Ferrell 1996). As suggested by Gwinner et al. (2005, p. 133) "truly adaptive behavior is not always "personal"; rather, it is contingent on the customer's current desires". Thus, adaptiveness can be different from service personalization (e.g., small talk, polite behavior, or using the customer's name) (Gwinner et al. 2005). In fact, interpersonally adapting the relationship can involve being "personal" if the customer desires a personal interaction and being "non-personal" if the customer does not desire that type of interaction (Gwinner et al. 2005). This could be applied in the case of relationships with conversational agents where individuals might prefer more or less personalized, human-like conversation according to the tasks characteristics and task type (Köhler et al. 2011; Longoni and Cian 2020). For instance, social contents might be less preferred than functional content in the contexts of economic transactions, leading to less-than-optimal customer decision making, misunderstanding or discomfort (Köhler et al. 2011; Mende et al. 2019). However, in contexts where empathy is considered as an important factor, higher levels of social content and personalization may be preferred leading to higher trust (Köhler et al. 2011; Longoni and Cian 2020; Mende et al. 2019)

Thus, adaptability is fundamental in the buyer-seller relationships, increasing trust and relationship longevity thanks to its ability to target individuals meeting their requirements (Day and Montgomery 1999; Gwinner et al. 2005). However, the implementation of chatbots, which often follow predetermined rules, challenge the firm's ability of creating unique, adaptive relationships which take into account consumers' needs. Also, the lack of empathy and authenticity can negatively affect the perception of the interaction with conversational agents. As suggested by Van Pinxteren et al. (2020), these forms of services are often experienced as impersonal and lacking human touch. As suggested by Hennig-Thurau et al. (2013), social communication is valuable when perceived as authentic. However, value offered by customer relationship management - such as conversational agents - could be perceived as a "short-lived gimmickry" (Hennig-Thurau et al., 2013, p.239). In addition, as AI is perceived as unable to relate with consumers, it can undermine consumers' feelings of sense of uniqueness, thus creating negative perceptions (Longoni et al. 2019).

5.3. Ethical Concerns and Trust

If on the one hand chatbots are perceived as unethical because of their inability to truly understand individual needs, following standardized rules and not being able to "get out of the paths they have in their memory"; on the other hand, autonomous cars are perceived as unethical if their algorithms are not standardized and do not follow the same code of conduct in all situations. In order to increase trust, chatbots 'algorithms need to be programmed in a way the interaction is perceived as unique, being able to take into account consumers' individual needs. Thus, adaptability plays a key role in increasing trust towards the conversational agent. On the contrary, in order to be perceived as trustworthy, autonomous vehicles 'algorithms need to follow standardized rules. Their ethical design needs to be clearly and unanimously defined by regulators. Thus, we find an opposite perception of the effect of adaptability versus standardisation of algorithms in chatbots and autonomous vehicles. In addition, safety benefits associated to autonomous cars might increase trust towards the autonomous vehicles. As suggested by Hengstler et al. (2016), safety is necessary to initiate performance trust. However, consistently with Shariff et al. (2021), our results show that consumers might have unrealistic safety threshold which need to be carefully considered.

In addition, our study suggests that when discussing autonomous vehicles, cognitive trust, characterised by the beliefs that the car is going to perform in a reliable manner (Glikson and Woolley 2020) seems to be predominant. However, when discussing trust towards chatbot, the emotional components of trust seem to prevail. In fact, the emotional design and the relational component of the interaction related to the need of adaptability emerge as important topics, driving trust. In this regard, Glikson and Woolley (2020), highlight the role that AI's anthropomorphism plays specifically for emotional trust (Glikson and Woolley 2020). The higher resemblance of conversational agents with humans might explain why emotional components of trust are predominant when discussing this type of technology. The results, however, also suggest a trade-off between the lack of emotions and the efficiency of chatbots, which is positively perceived having a significant positive effect on trust. In this regard, despite many studies show the importance of humanizing the machine through emotions to increase trust, our results are in line with a growing number of researches suggesting that implementing emotions in machines could generate negative reactions such as discomfort (Go and Sundar 2019; Liu and Sundar 2018; Mende et al. 2019; Murtarelli et al. 2021). Depending on the domain, consumers might prefer a competent, efficient chatbot instead of an unrealistic, inauthentic "emotional" bot. To conclude, both studies highlight the significant effect of trust on the intention to use the technology.

6. Theoretical Contributions

On a theoretical level the studies contribute to the growing marketing literature on AI ethics shedding light on consumers 'ethical perceptions of different AI products (Du and Xie 2020; Murtarelli et al. 2021). In particular, we show that when discussing ethical concerns and trust towards AI, researchers should take into account the wide spectrum of AI techniques and the different product characteristics. In fact, according to the different product inner characteristics, different ethical concerns and different component of trust emerge. Thus, we also contribute to the literature on trust toward AI in two ways (Glikson and Woolley 2020). First, we highlight the link between ethics and trust, which is fundamental to drive acceptance of these new disruptive technologies (Argandoña 1999). Second, we show that according to the type of technology, emotional or cognitive components of trust might be more prominent. When discussing chatbots, for instance, emotional trust might play a key role, as individuals highlight the importance of the emotional design of the machine and the need of developing individualized relationships. When discussing autonomous vehicles, cognitive aspect of trust related to the beliefs of safety and reliability of the technology emerge.

To conclude, the innovative methodology applied in the study offer new insights on the topic, providing explorative empirical evidence of consumer ethical concerns. Since many studies on AI ethics are mainly conceptual (Bostrom and Yudkowsky 2011; Du and Xie 2020b; Jobin et al. 2019; Murtarelli et al. 2021), we respond to the need of conducting more empirical research by adopting a pragmatic approach and investigating ethics from the consumers' point of view.

7. Managerial Implications

On a managerial level, we offer insights to increase trust and intention to use the technology by addressing customers' ethical concerns according to the different AI-products' characteristics. When implementing chatbots, managers need to consider the interactivity and immediacy behaviors of the technology, addressing the risk of human replacement, the emotional design, the privacy concerns and the need of adaptation as critical concerns. Components of emotional trust might to be predominant in consumers' minds. In this regard, in order to increase trust, managers should carefully balance chatbots' emotional reactions, which may be perceived as unethical. Depending on the context, efficiency may be preferred to unreal and inappropriate emotional reactions of the chatbot. In addition, particular attention needs to be given to the consumer-bot relationship, trying to comprehend and address consumers 'individual needs. In fact, despite chatbots can benefit the company by offering more efficient services, the lack of adaptability can backfire the firm, being detrimental for developing long-term and trustful relationships with consumers.

When implementing autonomous cars, managers need to address instead ethical concerns linked to the higher level of intelligence and critical decision making such as the ethical design, the transparency of the algorithm, road safety and accessibility. In particular, consumers needs to understand the rules behind algorithmic decision making, being informed about how their data are processed and being reassured about the standard followed by algorithms. In order to increase trust, the ethical design behind algorithm decision making should follow clear and standardized regulations. Also, road safety benefits can increase trust. However, managers need to carefully design communication around safety benefits, because consumers might have unrealistic expectations. We suggest that when discussing autonomous cars, cognitive components of trust in term of safety and reliability are predominant.

8. Limitations and Future Research Directions

Our studies highlight ethical concerns of two different European samples which could have different perceptions of ethics. In addition, the samples used in the studies are not representative. Further studies should replicate these results with representative samples from the same countries. In addition, since ethical concerns are culturally mediated (Bonnefon et al. 2016), ethical perceptions might be significantly different between European and non-European countries. Thus, further studies could also extend our approach to other non-

European countries where ethical concerns may differ according to different moral rules and standards. Collectivistic countries, for instance, could have different perceptions of ethics than individualistic countries (Bonnefon et al. 2016). Besides, we did not control for individual characteristics, which could play a role in affecting ethical concerns. Thus, further studies should consider the role of individual characteristics such as the educational level or the degree of innovativeness in affecting ethical concerns and trust.

In addition, our models may not cover other relevant ethical issues which did not emerge from our data due to the explorative nature of the research. Future studies could collect more data from other sources such as social networks and website around the globe to confirm and enrich our findings. We also suggest that further research should investigate what kinds of regulations and policies are needed to deal with the topics that have emerged in these studies and how these regulations would be perceived by consumers. In particular, regulations about privacy and transparency, as well regulations concerning the potential large-scale unemployment due to the implementation of bots and the ethical design of autonomous cars could be prominent issues worth being investigated.

Introduction

PART I
Defining AI in Marketing

Chapter 1. Artificial Intelligence in Marketing Research: Scientometric, TCCM Review and a Research Agenda

PART II
Practical AI Applications

Chapter 2. Rage Against the Machine: Investigating Consumers Negative Emotions, Attributions of Responsibility and Coping Strategies in AI-Based Service Failures

Chapter 3. Now, Take your Hands from the Steering Wheel! How Trust, Well-Being and Privacy Concerns Influence Intention to Use Semi- and Fully Autonomous Cars

PART III
On the Ethics of AI

Chapter 4. Consumers' Perspectives on AI Ethics and Trust: an Explorative Investigation of Ethical Concerns Towards Autonomous Cars and Chatbots

Overall Theoretical, Methodological, Managerial Contributions, Research Limits and Future Research Directions

OVERALL THEORETICAL, METHODOLOGICAL, MANAGERIAL CONTRIBUTIONS, RESEARCH LIMITS AND FUTURE RESEARCH DIRECTIONS

This research investigates consumers' behaviors when using and interacting with intelligent technologies. The first chapter is a conceptual paper where we conduct a hybrid literature review drawing from Paul and Criado (2020) and Vlačić (2021). After we select 167 peer-reviewed papers published in ranked marketing journals concerning artificial intelligence in marketing and consumer behaviors, we conduct a scientometric review to analyse the extensive number of peer-reviewed papers by using statistical tools such as R and Vosviewer (Visualization for Similarities), describing the evolution of the field and the scientific landscape. Next, we conduct an in-depth systematic review of the 167 selected papers, employing the Theory–Context–Characteristics–Methodology (TCCM) review protocol (Paul and Rosado-Serrano 2019; Rosado-Serrano et al. 2018), which sheds light on both theoretical and empirical aspects of a specific research domain. Thus, the in-depth analysis of the literature helped us to identify and define the research questions concerning 1) consumers' cognitive and emotional reactions when interacting with technologies that are able to simulate human-like conversations; 2) factors affecting consumers' intention to use AI-based technologies such as fully autonomous vehicles and their evolution across levels of automation; 3) consumers' ethical concerns towards AI products and their effect on trust and usage intentions.

To answers our research questions, we conduct empirical investigations on two current applications: autonomous cars and chatbots. Investigating these two different AI-based intelligent products allows us to take into account part of the wide spectrum of the existing AI techniques, analysing both verbal interactions and usage of AI in critical situations. In particular, in Study 1 of Chapter 2 (N = 122), we compare human–human and human–chatbot interactions, leveraging insights from Cognitive Appraisal Theory (Roseman 1991; Roseman et al. 1990) and Attribution Theory (Weiner 2000) to establish initial findings and a research framework. In Study 2 (N = 120), we extend this research framework to include anthropomorphic visual cues (high versus low) and the attribution of intentionality to the machine (Kervyn et al. 2012), identifying their effects on coping strategies. Finally, in Study 3 (N=120) we focus on attributions of responsibility to the company, according to the anthropomorphic visual cues of the chatbot.

In Chapter 3, we investigate the way consumers' experience with different levels of automation affect perceptions towards fully autonomous cars in relation to trust, well-being, privacy concerns and usage intentions (Bertrandias et al. 2021; Eggers and Eggers 2021; Hohenberger et al. 2017; Huang and Qian 2021). Drawing from Venkatesh and colleagues (Venkatesh et al. 2003, 2011), we integrate the UTAUT framework with Trust Theory (Mcknight 2005; Mcknight et al. 2011), Privacy Calculus Theory (Dinev and Hart 2006) and Theory of Well-being (Diener 1999; Diener and Chan 2011). Thus, we conduct four studies. First, we conduct an online survey (N=331) on fully autonomous cars to test our model with a representative sample of the German population. Second, we replicate the results through a survey with another sample in Germany (N=138). Third, by conducting a field study with a semi-autonomous car of level 2 (N=138), we implement with the same sample as in study 2 a within subject design investigating how consumers' perceptions of fully autonomous cars evolve before the driving experience and after a driving experience with a level 2 semi-autonomous car. Fourth, we conduct a simulator study (N=138) to investigate how consumers' perceptions of fully autonomous cars evolve from experiencing level 2 to level 5 of automation. The within subject approach (study 2 to study 4) allows us to comprehend how perceived trust, privacy concerns, well-being and usage intention of fully autonomous cars change and evolve across the development stages and levels of automation, offering insights for future research and practitioners. In Chapter 4, we finally investigate consumers' ethical concerns surrounding AI. We employ a mixed methods research approach. First, we use topic modeling to get insights about ethical concerns towards autonomous cars (Study 1, N=138) and chatbots (Study 2, N=161). Second, we implement structural equation modeling to predict the effect of ethical concerns on trust and intention to use the technologies.

1. Theoretical Contributions

1.1. Mapping the Scientific Landscape

Through our hybrid literature review, we contribute to the theory by providing foundation of knowledge on the topic related to AI in marketing, identifying areas of prior scholarship and research gaps that justify the need for future investigations. In particular, through the scientometric approach, we identify seven clusters of research streams: 1) AI techniques and applications 2) human-AI interactions in service settings, 3) AI ethics 4) consumers' behaviors and psychology in the era of AI 5) AI, company transformation and digitalization, 6) AI and social media management 7) AI, e-commerce and financial services. By systematically investigating each research stream though the TCCM approach, we unveil the theories that underpin each research stream, defining and clarifying the main concepts. In particular, by reviewing the marketing papers in the first cluster, we clarify the concepts and definitions of AI techniques such as machine learning, deep learning, neural network, natural language processing and recommendation system, shedding light on their current marketing applications. By reviewing the papers of the second cluster, we define AI in service settings. In particular, we clarify the different definitions of service robots, virtual agents, virtual assistants, and conversational agents, and we identify and review the main theories used in this particular stream of research, such as Anthropomorphism Theories (Aggarwal and McGill 2007; Epley et al. 2007), Social Perception Theories (Fiske et al. 2007) and Theories of Job Replacement (Huang and Rust 2018). In the third cluster, we contribute to the literature on AI ethics, extending the model of Du and Xie (2020), investigating ethical challenges of AI products at the product-level, consumer-level, company-level and society-level. In the fourth cluster we categorize the papers exploring consumer's behaviors and psychology around AI, identifying the more recurrent research topics, in particular technology adoption and acceptance (Davis 1980; Parasuraman 2000); consumer decision making (Klaus and Zaichkowsky 2020); consumers engagement and satisfaction with AI applications (Hollekeek et al. 2021). In the fifth cluster we also identify and describe the way companies use AI. In particular, we identify 3 main sub-topics: 1) company decision making augmented by AI 2) business models adaptation and digitalization 3) AI, marketing and service strategies. For each sub-topic, we give a systematic overview which help to conceptualize and formalize the existent literature. Finally, we review the literature on AI-based social media management (cluster 6) and e-commerce and AI-based financial services (cluster 7), also in this case defining the main research topics, approach and methodologies used. This literature review gives a strong contribution to the literature on AI by classifying and categorizing the complex AI research landscape. Thus, we contribute by helping current researchers to better navigate this deep and multi-layered topic. In addition, we suggest a research agenda for each research stream, presenting potential research questions for future research.

1.2. Emotional and Cognitive Responses When Using and Interacting with Different AI Applications

By empirically investigating consumers' emotional and cognitive responses when using and interacting with intelligent technologies we contribute to the emerging literature of AI-based service and to consumer behaviors theories related to AI (Davenport et al. 2020; Huang and Rust 2018; Meyer-Waarden et al. 2020; Wirtz et al. 2018). In particular, Chapter 2 shows that consumers' emotional responses differ when interacting with a human and a chatbot, according to the different attributions of responsibility. On the one hand, when interacting with AI-based chatbots, customers attribute more responsibility to the company; experiencing higher frustration about the negative situation that they cannot control. On the other hand, when interacting with human agents, the attribution of responsibility includes the employees and the company, increasing customers' anger toward the human agent blamed for the poor service (Bonifield and Cole 2007; Gelbrich 2010). Since a chatbot is not directly accountable for the outcome, consumers blame the company because of its decision of implementing the automated service. However, attributing anthropomorphic visual cues to the chatbot might help to mitigate the negative attributions to the company, increasing the attribution of responsibility to the machine. Thus, anthropomorphism can activate human schemas in the interaction, potentially affecting also the way consumers experience and regulate emotions (Go and Sundar, 2019; Golossenko et al. 2020). In this regard, out results suggest that anthropomorphism can also affect emotional regulation. In particular, we show that the perception of the communication partner as being able to plan and implement his or her own intentions influences the use of confrontational coping strategies. This effect is stronger when the agent is highly anthropomorphized. Thus, we enrich the existent literature on coping strategies applied to technology (Beaudry and Pinsonneault 2005; Gelbrich 2010; Mick and Fournier 1998) showing that anthropomorphizing the chatbot might foster confrontive problem-focused coping strategies (Gelbrich 2010; Roseman 1991). We also contribute to Attribution Theory (Weiner 2000) by shedding light on how attributions of responsibility toward service agents and firms change depending on the identity of the service providers. In addition, we also contribute to Anthropomorphism Theories by showing that anthropomorphism can affect the perceptions of responsibility and the emotional reactions (Aggarwal and McGill 2007; Araujo 2018; Blut et al. 2021; Epley et al. 2018; Go and Sundar 2019; Lee 2010).

If on the one hand when investigating chatbots consumers tend to more easily attribute responsibility for the negative outcome; on the other hand, results of Chapter 4 suggest that when investigating autonomous vehicles, the discussion around the attributions of responsibility and liability in case of failure is more complex. In particular, consumers struggle to clearly attribute responsibility for a failure during the driving tasks, indicating either the company, either the software developer, either the driver as potential responsible. In this regard our studies highlight that clarifying attributions of responsibility in case of accidents is one of the fundamental step in reducing the uncertainty surrounding the implementation and adoption of these technologies (Awad et al. 2018).

In addition, the results of Chapter 2 suggest that anthropomorphism can affect the way consumers attribute blame in the case of a technological failure. Thus, we propose that also in the context of autonomous vehicles, anthropomorphizing a car, for instance by integrating a voice-based assistant that is able to mimic human-like verbal interactions, might potentially have an effect on the attribution of responsibility by activating human schema and developing a feeling of social connection. In this regard, Waytz et al. (2014) already suggest that anthropomorphizing a car with enhanced humanlike features (name, gender, voice) might decrease attributions of responsibility to the car and related entities in case of accident. However, this effect needs to be further tested and validated.

1.3. Emotional and Cognitive Responses Across Different Levels of Automation

Our research also offers contributions to the emerging literature on consumer behaviors related to intelligent products such as autonomous cars and chatbots, by highlighting the need to take into account the complexity of AI technologies across their development stages and levels of automation (Bertrandias et al. 2021; Huang and Quian 2021; Puntoni et al. 2021). In this regard, differentiating between the different automation levels helps to better understand the potential drivers of adoption as well as the cognitive and emotional reactions when interacting and using intelligent applications. In fact, since autonomous technologies are gradually brought into the market, customers will have the chance to construct their beliefs and perceptions over time, gradually experiencing higher levels of automation (Menon et al. 2020). In this regard, in the context of autonomous cars, we provide evidence that experiencing the functions across level 2 and level 5 might help clarifying how they can positively affect consumers' quality of life, increasing the ease of use related to the technology, the trusting beliefs of helpfulness and reliability, and decreasing the privacy concerns related to the technology. In addition, the more individuals experience autonomous cars' functions, the more they trust them to have the ability to deliver the functionalities promised, increasing the behavioral intention to use it. Thus, we contribute to the literature on technology adoption identifying both the cognitive beliefs and psychological drivers of adoption by integrating the traditional UTAUT framework (Venkatesh et al. 2003) with psychological Theory of Well-being (Diener 1999; Diener and Chan 2011), Privacy Calculus Theory (Dinev and Hart 2006) and Trust towards Technology (McKnight et al. 2011) across levels of automation. We show that well-being can be a fundamental driver of usage. In particular, we suggest that a successful driving performance might relieve consumers from the stress related to the driving task, offering a more pleasant and enjoyable experience, increasing usage intention. Besides, we also contribute to the literature on trust towards technology (McKnight 2011) and well-being (Diener 1999; Diener and Chan 2011; Meyer-Waarden and Cloared 2021; Sirgy et al. 2012) emphasizing the role of the cognitive trusting beliefs of helpfulness, functionality and reliability in increasing perceived well-being. In particular, the more individuals perceive the technology as predictable, functional and helpful in executing the driving tasks, the more their perceptions of happiness and life satisfaction are fulfilled, increasing the intention to use the technology.

Also in the case of chatbots, the different levels of intelligence might affect consumers' emotional and cognitive responses. In fact, as suggested by Huang and Rust (2018), chatbots can have four different levels of intelligence: the mechanical, the analytical, the intuitive, and the empathetic. At the mechanical and analytical levels, the machine is still not capable to understand and deal with complex situations, for instance involving consumers' emotions. In this regard, as shown in Chapter 2 and Chapter 4, the lack of chatbots' emotional understanding might result in consumers' frustration, potentially decreasing their well-being and affecting the way consumers intend to use the technology (Diener 1984; Frow et al. 2019). However, our studies show that, if on the one hand the lack of empathy and emotions can be negatively perceived, on the other hand, developing chatbots able to express and simulate emotions might induce feeling of discomfort and creepiness. Thus, we suggest that at their current level of mechanical and analytical intelligence, the trade-off between lack of emotion and efficiency might be preferred to unauthentic expressions of emotions (Meyer-Waarden et al. 2020).

1.4. Consumers Perspectives on the Ethics of AI

Investigating AI-technologies also implies a consideration of the ethical issues that the technology raises. Thus, on a theoretical level, we contribute to the growing marketing literature on AI ethics shedding light on consumers 'ethical concerns of different AI-based products, in particular autonomous cars and chatbots (Du and Xie 2020; Murtarelli et al. 2021). We show that researchers must consider the vast and different range of AI techniques, as well as the different product features, when discussing ethical issues and trust towards AI. For instance, we show that for chatbots, the interactional and emotional component of the technology is predominant, raising ethical concerns related to the emotional design of the machine, the adaptability of the human-bot relationship, the human replacement and the privacy concerns. We suggest the ethical concerns related to the emotional component of the technology might be explained by the higher degree of anthropomorphism of the machine (Glikson and Woolley 2020). However, for autonomous cars, the ethical concerns rather involve cognitive perceptions related to the transparency of the algorithms, the ethical design, the safety of the technology and the accessibility. By investigating the effect of the ethical concerns on perceived trust, we also contribute to the literature on trust towards AI in two ways (Glikson and Woolley 2020). First, we highlight the link between ethics and trust, which is fundamental to drive acceptance of these new disruptive technologies (Argandoña 1999). Second, we show that according to the type of technology, emotional or cognitive components of trust might be more prominent. For chatbots, for instance, emotional trust might play a key role, as individuals highlight the importance of the emotional design of the machine and the need of developing individualized relationships. For autonomous vehicles, the cognitive aspect of trust related to the beliefs of safety and reliability of the technology emerge.

To conclude, since many studies on AI ethics are mainly conceptual (Bostrom and Yudkowsky 2011; Du and Xie 2020b; Jobin et al. 2019; Murtarelli et al. 2021), we contribute to the existent literature by adopting a pragmatic approach and providing empirical insights on consumers' perceptions of ethics and trust towards AI technology.

2. Methodological Contributions

2.1. Mixed Method Approaches

Methodological contributions relate to the mixed methods approaches used in Chapter 1 and Chapter 4. In particular, the mixed approach used in Chapter 1 allows us to investigate the literature both at the macro-level and micro-level. In this regard, scientometric helps us to map the scientific landscape at the macro-level, describing the evolution of the field and identifying the main research streams related to AI (van Eck and Waltman 2010). The TCCM method, instead, allows us to investigate each research stream at the micro-level, describing in detail the main theories, the contexts and the methodologies applied (Paul and Rosado-Serrano 2019; Rosado-Serrano et al. 2018). To our best knowledge, this is the first time that such a hybrid approach has been implemented to investigate the literature. We also adopt an innovative methodological approach in Chapter 4, where we combine both qualitative and quantitative approaches implementing topic modeling and structural equation modeling (SEM). This explorative approach is useful to get insights on new topics such as consumers' ethical concerns around AI and to predict their effects on well-established constructs such as trust and intention to use. In particular, topic modeling is a text-mining tools useful to identify latent structures in a text body (Berger et al. 2020; Humphreys and Wang 2018). Thus, we firstly use topic modeling to get insights on consumers' ethical concerns related to autonomous cars and chatbots defining the new topics. Next, we use SEM, a statistical modeling method used to investigate relationships among observed and latent constructs, testing the effects of the new topics on the well-established constructs of trust and intention to use.

2.2. Experimental Design, Field and Simulator Studies

The methodological contributions of the thesis also include the implementation of innovative experimental research designs, using advanced tools and applications. In particular, in Chapter 2 we increase the credibility of the scenarios designing an interactive video simulating the interaction with an AI-based chatbot. The video-based approach is useful to create a more realistic environment when testing interactions with the technology. We also offer methodological contributions in Chapter 3 where we implement a within-subject design, integrating field and simulator studies to investigate consumers' responses to increased levels of automation. We suggest that such «dynamic » approaches can generate more in-depth insights compared to dominant « static » approaches focusing only on one level of automation. In addition, facing respondents with real field and simulator studies (e.g. a real semi-autonomous car of level 2 and a simulator of a fully autonomous car of level 5) enables us to overcome the limitations of predominant online surveys and scenarios, which are not able to take into account and reflect non-existing abstract disruptive technologies such as fully autonomous cars. In fact, as suggested by Kempf (1999) and Smith (1993), direct experience through field experimentations and product trials is a stronger and more realistic predictor of consumers' behaviors than indirect experience through surveys. Above all when investigating new disruptive technologies, repeated experiences with the new product are fundamental to comprehend how consumers' perceptions are shaped and change.

3. Managerial Implications

Implementing AI technologies requires the attention of managers and practitioners who should carefully take into account consumers' needs to guarantee successful and positive interactions with the technology. We offer managerial insights for managers who want to implement conversational agents in service settings and managers who operate in the contexts of complex autonomous technologies such as autonomous vehicles.

3.1. Managerial Implications for Conversational Agents in Service Settings

Despite efficiency can be a clear advantage of implementing AI in customer services through chatbot and conversational agents, particular attention needs to be given to the relationship that is built with consumers. AI technologies often lack the empathetic and intuitive intelligence necessary to understand consumers' emotions and to offer authentic experiences. For this reason, the implementation of chatbots in complex situations such as service failure can have negative repercussions for the firms, such as higher attributions of responsibility to the company, consumers' negative emotions and lack of trustful and long term relationships. Our study suggests that anthropomorphizing the machine can help to mitigate negative attributions to the firm and to foster problem-focused coping strategies, activating human schema. In fact, creating a sense of human connection, so that consumers believe they are in the presence of another social entity (van Doorn et al. 2017), may mitigate negative attributions and help consumers to deal with negative situations. However, as consumers might also experience negative emotions when interacting with intelligent technologies, we suggest that companies need to find a way to actively deal with customers' negative emotional reactions. Nevertheless, considering that chatbots are still not enough developed to truly understand consumers' feelings and answer adequately, we suggest that simulating emotions and empathy could be perceived as unethical because lacking of authenticity. Thus, while waiting that the technology becomes sufficiently mature to deal with consumers' emotions; companies need to find the optimal balance between "tech" and "touch" in service encounters (Giebelhausen et al. 2014). In simple contexts, service managers should assign chatbot agents to deal with non-complex repetitive situations which can be better managed without emotions by robots. For example, information research and collection and first interactions with customers could be those tasks. On the other hand, in complex situations such as failure or double deviation, service managers should assign human agents to deal with consumers' emotional reactions and to create meaningful relationships. In fact, consumers are concerned about the lack of adaptability and personalization of the automated services. Since chatbots fail to comprehend and address consumers 'individual needs, the relationships with consumers might suffer. Besides, managers should also address consumers' privacy concerns related to the implementation of AI-based service agents and the perceived risk of human replacement. As suggested by previous research, companies could benefit from CSR practices aiming to inform consumers on the way their data are used and on the way potential unemployment due to automation is addressed (Du and Xie 2020).

3.2. Managerial Implications for Autonomous Vehicles

Our studies also suggest that technologies that involve decision making in critical situations such as autonomous cars can also raise other type of concerns. In this regard, if on the one hand when talking about chatbots the emotional and interactional components of the technology emerge, on the other hand, when talking about autonomous vehicles, the cognitive beliefs related to the reliability and safety of the technology seem to be predominant. We suggest that experiencing the technology through product trial helps to shape stronger consumers' beliefs. For instance, when experiencing level 2 and level 5 of automation, consumers' trusting beliefs towards fully autonomous cars and behavioral intention to use the technology increase. The more consumers experience increasing levels of automation, the more they might get confident about the autonomous cars 'abilities to drive effectively and properly (McKnight et al. 2011). In addition, the level of opacity around autonomous functions, which makes them appear unpredictable and untrustworthy in many circumstances, can be overcome through deeper experiences with functions having a higher level of autonomy. In fact, both the ease of use and the usefulness of the features increase as users experiment higher levels of automation. In addition, consumers highlight the lack of transparency behind algorithmic decision making as a critical ethical concern. Thus, managers should address this issue in order to implement technologies that are perceived as more ethical, being clear and transparent about the rules that define the algorithms and clarifying how consumers' data are collected, processed and used.

In addition, we suggest that in order to increase trust and usage intentions of fully autonomous vehicles managers should emphasize the way autonomous functions might increase consumers' well-being. In this regard, our studies show that consumers often doubt how fully autonomous vehicles could benefit them in term of improved well-being and quality of life. For this reason, managers could implement communication campaigns to better explain the benefits of fully autonomous vehicles in terms of increased well-being and life satisfaction. In this regard, the safety benefits could also contribute to increase trust and intention to use autonomous vehicles. However, managers should be careful when communicating the safety benefits of autonomous cars. In fact, people require higher levels of safety from autonomous cars than humans, having much more stringent and unrealistic safety thresholds related to autonomous cars. In this regard, our study suggests that consumers would use autonomous vehicles only if the "security is 100% guaranteed". This unrealistic safety threshold might slow down the introduction of autonomous cars in the market, as they might not meet consumers' expectations. Managers could address this issue by pointing out that, while perfecting AV technology, society could already reap the potential benefits of using autonomous cars that are already safer than the "average" human driver. In conclusion, when discussing autonomous vehicles, officials could also highlight accessibility and greater mobility for the disabled and elderly as strength of autonomous vehicles. However, consumers are also concerned about the risk of inequalities and low accessibility of autonomous mobility for low-income people and countries, due to the higher prices of the technology. In this regard, companies in the automotive industry should think about potential solutions (e.g. tailored business models) to ensure access to autonomous mobility also for low-income groups.

4. Implications for Policymakers

AI-based intelligent technologies are going to reshape our society thanks to their abilities to harvest data and make critical decisions. In this context, policymakers need to implement effective regulations and policies that take into account the challenges that each AI- technology raises according to its specific characteristics.

We suggext that human replacement should be considered a key issue both in the case of conversational agents and autonomous vehicles. Regulators could explore new policies to address potential large-scale unemployment or underemployment, also discussing training programs and fundings for those who might lose their jobs and for the new workforce of tomorrow. In addition, as suggested by Du and Xie (2020), tax systems may also require adjustments to ensure long-term solvency as more and more segments of the workfoce are replaced by automation. Similarly, regulations on how data are collected and processed should be constantly updated to meet the challenges of rapidly evolving technologies.

In addition, consumers emphasize the need of having standardized, international regulations that define the way intelligent technologies make decisions in critical situations and the way the responsibility is attributed in case of accidents. In this regard, in the case of autonomous vehicles, consumers identify either the manufacturer, either the software developer, either the driver, as potential responsible in case of accident with fully autonomous cars. However, the lack of clarity around liability issues needs to be addressed at international levels by policy-makers and regulators. As the institutional environment significantly differs across countries, an international debate should be raised. In addition, regulators should discuss policies to guarantee the transparency behind the algorithm decision-making process.

5. Limitations and Further Research Directions

Despite we already present a rich research agenda in Chapter 1, the studies discussed in Chapter 2, Chapter 3 and Chapter 4 present some limitations that offer new path for future research.

In particular, the experimental design of the three studies presented in Chapter 2 does not allow testing human-chatbot interactions in real-world conditions. Thus, we suggest that further research should investigate interactions with real AI-based chatbots in actual service failures, for instance by using field studies. In addition, besides using declarative data, also behavioral data should be used to better comprehend users'behaviors and emotional reactions. For instance, researchers could use neuro-marketing tools such as EEGs (electroencephalograms) to read brain-cell activities and facial-expression codings (reading the movement of muscles in the face) to measure emotional responses (Harrell 2019). In this way, other emotional reactions could be investigated, enriching our studies where we only focused on two specific emotions, namely anger towards the agent and frustration with the situation. Given the negative emotional reactions, the potential consequences on consumers' well-being and satisfaction should also be studied empirically.

In addition, we only investigate a double deviation situation in the airline context. So, the results cannot be generalized to other service contexts. For this reason, further research should also address other service industries where the interactions with AI-technology could be differently perceived, such as healthcare, banking services or more symbolic consumption contexts such as art and cultural sectors or beautycare (Granulo et al. 2021; Longoni and Cian

2020). Since we did not consider many characteristics of consumers and chatbots, we also suggest extending our research framework to specify boundary conditions, such as those related to the conversational styles or personality traits of consumers and/or chatbots.

The investigation on autonomous cars presented in Chapter 3 also has some limitations that should be taken into account. First, we conduct the study in Germany, thus focusing the context of our analysis on a specific country. Other research could take a cross-cultural approach, replicating our study in different countries and highlighting the cultural differences that affect adoption (Edelmann et al. 2021; Rhim et al. 2020). We find the same limitation in Chapter 4, where we have a German and a French sample. Here again, ethical concerns need to be addressed at different national and international levels, as they might be culturally mediated. The second limitation of Chapter 3 concerns the driving simulator. Indeed, despite the numerous advantages of using a driving simulator, such as the controllability and reproducibility of the environment as well as the possibility of testing a disruptive technology that is not yet ready on the market, there are also some disadvantages: in particular, the limited perceptual fidelity with the real context and the lower perceived personal risk (De Winter et al. 2012). Thus, further empirical research should ideally replicate our results with a real level 5 fully autonomous car (which is not an easy task, as they only exist in certain limited geographical areas and contexts). In addition, as we mainly investigate the perception towards autonomous vehicles from a cognitive perspective, further studies should also investigate the emotional components of trust and acceptance towards fully autonomous cars. In this case, too, behavioral data could be collected. In both Chapter 3 and Chapter 4, we do not consider users' psychological traits, such as innovativeness, referring to the probability of a person being willing to try a new technology (Rogers 1995; Steenkamp and Gielens 2003), which could affect the way individuals perceive the technology and how they take risks (Huang and Qian 2021). To overcome this issue, we suggest that future research should investigate such boundary conditions. Furthermore, as autonomous cars are likely to be equipped with voice assistants, the effect of anthropomorphizing the car and its voice on trust, behavioral intentions and ethical concerns could be further investigated (Aggarwal and McGill 2007).

With respect to Chapter 4, in addition to the limitations mentioned above, we suggest that our models may not cover other relevant ethical issues that did not emerge in our data. Future research should collect data from other sources such as social networks and website around the world to confirm and enrich our results. In addition, how consumers might perceive AI regulations and policies related for instance to privacy, transparency, liability and unemployment could be studied.

Finally, we call for more research adopting a "developmentally sensitive" research design for other innovation application contexts as well, taking into account the different development stages and levels of automation of new AI technologies and investigating how consumer perceptions change with experience and over time.

References

Abramova, E., & Slors, M. (2019). Mechanistic explanation for enactive sociality. *Phenomenology and the Cognitive Sciences*, *18*, 401–424.

Adner, R. (2017). Ecosystem as Structure: An Actionable Construct for Strategy. *Journal of Management*, *43*, 39–58.

Aggarwal, P., & McGill, A. L. (2007). Is That Car Smiling at Me? Schema Congruity as a Basis for Evaluating Anthropomorphized Products. *Journal of Consumer Research*, *34*, 468–479.

Ajzen, I. (1985). From Intentions to Actions: A Theory of Planned Behavior. In J. Kuhl & J. Beckmann (Eds.), *Action Control: From Cognition to Behavior* (pp. 11–39). Berlin, Heidelberg: Springer.

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, *50*, 179–211.

Ajzen, L., & Fishbein, M. (1980). *Understanding Attitudes and Predicting Social Behavior*. Englewood Cliffs, New Jersey: Prentiss-Hall.

Albrecht, T., Rausch, T. M., & Derra, N. D. (2021). Call me maybe: Methods and practical implementation of artificial intelligence in call center arrivals' forecasting. *Journal of Business Research*, *123*, 267–278.

Allal-Chérif, O., Simón-Moya, V., & Ballester, A. C. C. (2021). Intelligent purchasing: How artificial intelligence can redefine the purchasing function. *Journal of Business Research*, *124*, 69–76.

Alpar, P. (1991). Knowledge-based modeling of marketing managers' problem solving behavior. *International Journal of Research in Marketing*, *8*, 5–17.

Al-Shihabi, T., & Mourant, R. R. (2003). Toward More Realistic Driving Behavior Models for Autonomous Vehicles in Driving Simulators. *Transportation Research Record*, *1843*, 41–49.

Anderson, C., & Galinsky, A. (2006). Power, optimism, and risk-taking—Anderson. *European Journal of Social Psychology*, p. 36 (4) 511-536.

Anderson, L., Ostrom, A., Corus, C., Fisk, R., Gallan, A., Giraldo, M., Williams, J. (2013). Transformative service research: An agenda for the future. *Journal of Business Research*, *66*, 1203–1210.

André, Q., Carmon, Z., Wertenbroch, K., Crum, A., Frank, D., Goldstein, W., … Yang, H. (2018). Consumer Choice and Autonomy in the Age of Artificial Intelligence and Big Data. *Customer Needs and Solutions*, *5*, 28–37.

Angeli, A. D., & Brahnam, S. (2008). I hate you! Disinhibition with virtual partners. *Interacting with Computers*, *20*, 302–310.

Angst, C. M., & Agarwal, R. (2009). Adoption of Electronic Health Records in the Presence of Privacy Concerns: The Elaboration Likelihood Model and Individual Persuasion. *MIS Quarterly*, *33*, 339–370.

Araujo, T. (2018). Living up to the chatbot hype: The influence of anthropomorphic design cues and communicative agency framing on conversational agent and company perceptions. *Computers in Human Behavior*, *85*, 183–189.

Argandoña, A. (1999). Sharing Out in Alliances: Trust and Ethics. *Journal of Business Ethics*, *21*, 217–228.

Aria, M., & Cuccurullo, C. (2017). bibliometrix: An R-tool for comprehensive science mapping analysis. *Journal of Informetrics*, *11*, 959–975.

Awad, E., Dsouza, S., Kim, R., Schulz, J., Henrich, J., Shariff, A., Rahwan, I. (2018). The Moral Machine experiment. *Nature*, *563*, 59–64.

Awad, E., Levine, S., Kleiman-Weiner, M., Dsouza, S., Tenenbaum, J. B., Shariff, A., Rahwan, I. (2018). Blaming humans in autonomous vehicle accidents: Shared responsibility across levels of automation. *ArXiv:1803.07170 [Cs]*.

Bagozzi, R. P., Belanche, D., Casaló, L. V., & Flavián, C. (2016). The Role of Anticipated Emotions in Purchase Intentions. *Psychology & Marketing*, *33*, 629–645.

Bagozzi, R. P., Gopinath, M., & Nyer, P. U. (1999). The role of emotions in marketing. *Journal of the Academy of Marketing Science*, *27*, 184–206.

Balakrishnan, J., & Dwivedi, Y. K. (2021). Role of cognitive absorption in building user trust and experience. *Psychology & Marketing*, *38*, 643–668.

Balducci, B., & Marinova, D. (2018). Unstructured data in marketing. *Journal of the Academy of Marketing Science*, *46*, 557–590.

Bandura, A. (1986). Self-efficacy. *Prentice-Hall Series in Social Learning Theory*.

Banker, S., & Khetani, S. (2019). Algorithm Overdependence: How the Use of Algorithmic Recommendation Systems Can Increase Risks to Consumer Well-Being. *Journal of Public Policy & Marketing*, *38*, 500–515.

Baray, J., & Pelé, M. (2020). A new geographical pricing model within the principle of geomarketing-mix. *Recherche et Applications En Marketing*, *35*, 29–51.

Battisti, S., & Brem, A. (2020). Digital entrepreneurs in technology-based spinoffs: An analysis of hybrid value creation in retail public–private partnerships to tackle showrooming. *Journal of Business and Industrial Marketing*.1-21.

Baum, S. D., Goertzel, B., & Goertzel, T. G. (2011). How long until human-level AI? Results from an expert assessment. *Technological Forecasting and Social Change*, 78, 185–195.

Bazilinskyy, P., & de Winter, J. (2015). Auditory interfaces in automated driving: An international survey. *PeerJ*, *1*, 13

Bazilinskyy, P., Petermeijer, S., Petrovych, V., Dodou, D., & de Winter, J. (2018). Take-over requests in highly automated driving: A crowdsourcing multimedia survey on auditory, vibrotactile, and visual displays. *Transportation Research Part F Traffic Psychology and Behaviour*, *56*, 82–98.

Beauchamp, T. L. (2010). *Standing on Principles: Collected Essays*. Oxford University Press.

Beggiato, M., & Krems, J. F. (2013). The evolution of mental model, trust and acceptance of adaptive cruise control in relation to initial information. *Transportation Research Part F: Traffic Psychology and Behaviour*, *18*, 47–57.

Beggiato, M., Pereira, M., Petzoldt, T., & Krems, J. (2015). Learning and development of trust, acceptance and the mental model of ACC. A longitudinal on-road study. *Transportation Research Part F: Traffic Psychology and Behaviour*, *35*, 75–84.

Belanche, D., Casaló, L. V., Flavián, C., & Schepers, J. (2020). Robots or frontline employees? Exploring customers' attributions of responsibility and stability after service failure or success. *Journal of Service Management*, *31*, 267–289.

Belk, R. (2016). Understanding the robot: Comments on Goudey and Bonnin (2016). *Recherche et Applications En Marketing*, *31*, 83–90.

Belk, R. W. (1988). Possessions and the Extended Self. *Journal of Consumer Research*, *15*, 139.

Belk, Russell. (2016). Understanding the robot: Comments on Goudey and Bonnin (2016). *Recherche et Applications En Marketing (English Edition) (Sage Publications Inc.)*, *31*, 83–90.

Bentler, P. M. (1990). Comparative fit indexes in structural models. *Psychological Bulletin*, *107*, 238–246.

Bentler, P. M., & Bonett, D. G. (1980). Significance tests and goodness of fit in the analysis of covariance structures. *Psychological Bulletin*, *88*, 588–606.

Berger, Jonah, Humphreys, A., Ludwig, S., Moe, W. W., Netzer, O., & Schweidel, D. A. (2019). Uniting the Tribes: Using Text for Marketing Insight. *Journal of Marketing*, *84*, 1–25.

Bertani, F., Ponta, L., Raberto, M., Teglio, A., & Cincotti, S. (2021). The complexity of the intangible digital economy: An agent-based model. *Journal of Business Research*, *129*, 527–540.

Bertrandias, L., Lowe, B., Sadik-rozsnyai, O., & Carricano, M. (2021). Delegating decision-making to autonomous products: A value model emphasizing the role of well-being. *Technological Forecasting and Social Change*, *169*, 120846.

Bitner, M. J., Booms, B. H., & Tetreault, M. S. (1990). The Service Encounter: Diagnosing Favorable and Unfavorable Incidents. *Journal of Marketing*, *54*, 71–84.

Bitner, M. J., Brown, S. W., & Meuter, M. L. (2000). Technology infusion in service encounters. *Journal of the Academy of Marketing Science*, *28*, 138.

Blut, M., Wang, C., Wünderlich, N. V., & Brock, C. (2021). Understanding anthropomorphism in service provision: A meta-analysis of physical robots, chatbots, and other AI. *Journal of the Academy of Marketing Science*, *49*, 632–658.

Bock, D. E., Wolter, J. S., & Ferrell, O. C. (2020). Artificial intelligence: Disrupting what we know about services. *Journal of Services Marketing*, *34*, 317–334.

Bonifield, C., & Cole, C. (2007). Affective responses to service failure: Anger, regret , and retaliatory versus conciliatory responses. *Marketing Letters*, *18*, 85–99.

Bonnefon, J. F., Shariff, A., & Rahwan, I. (2016). The Social Dilemma of Autonomous Vehicles. *Science*, *352*, 1573–1576.

Bonnin, G., & Alfonso, M. R. (2019). The narrative strategies of B2B technology brands. *Journal of Business and Industrial Marketing*, *34*, 1448–1458.

Borau, S., Otterbring, T., Laporte, S., & Fosso Wamba, S. (2021). The most human bot: Female gendering increases humanness perceptions of bots and acceptance of AI. *Psychology and Marketing*, *38*, 7, 1052-1068.

Bostrom, N. (2014). *Superintelligence: Paths, Dangers, Strategies* (Oxford University Press).

Bostrom, N., & Yudkowsky, E. (2011). *The Ethics of Artificial Intelligence*. 20.

Braganza, A., Chen, W., Canhoto, A., & Sap, S. (2020). Productive employment and decent work: The impact of AI adoption on psychological contracts, job engagement and employee trust. *Journal of Business Research*, *131*, 485-494.

Brill, T. M., Munoz, L., & Miller, R. J. (2019). Siri, Alexa, and other digital assistants: A study of customer satisfaction with artificial intelligence applications. *Journal of Marketing Management*, *35*, 1401–1436.

Brislin, R.W. (1980). Translation and content analysis of oral and written materials. *Methodology*, 389–444.

Brodie, R. J., Hollebeek, L. D., Jurić, B., & Ilić, A. (2011). Customer Engagement: Conceptual Domain, Fundamental Propositions, and Implications for Research. *Journal of Service Research*, *14*, 252–271.

Bromuri, S., Henkel, A. P., Iren, D., & Urovi, V. (2020). Using AI to predict service agent stress from emotion patterns in service interactions. *Journal of Service Management*.

Browne, M. W., & Cudeck, R. (1992). Alternative Ways of Assessing Model Fit. *Sociological Methods & Research*, *21*, 230–258.

Bruner, J. (1987). Life as narrative. *Social Research, 54, 11-32*.

Buchanan, B. G. (2005). A (Very) Brief History of Artificial Intelligence, *AI Magazine,* 26(4), 53-53.

Buhalis, D., Harwood, T., Bogicevic, V., Viglia, G., Beldona, S., & Hofacker, C. (2019). Technological disruptions in services: Lessons from tourism and hospitality. *Journal of Service Management*, *30*, 484–506.

Burström, T., Parida, V., Lahti, T., & Wincent, J. (2021). AI-enabled business-model innovation and transformation in industrial ecosystems: A framework, model and outline for further research. *Journal of Business Research*, *127*, 85–95.

Butt, A. H., Ahmad, H., Goraya, M. A. S., Akram, M. S., & Shafique, M. N. (2021). Let's play: Me and my AI-powered avatar as one team. *Psychology & Marketing*, 38(6), 1014-1025.

Bynum, T. W., & Rogerson, S. (2003). *Computer Ethics and Professional Responsibility | Guide books*. Blackwell Publishers, Inc. (world).

Byrne, B. M. (2006). *Structural equation modeling with EQS: Basic concepts, applications, and programming, 2nd ed* (pp. xii, 440). Mahwah, NJ, US: Lawrence Erlbaum Associates Publishers.

Cabanac, M. (2002). What is emotion? *Behavioural Processes*, *60*, 69–83.

Čaić, M., Odekerken-Schröder, G., & Mahr, D. (2018). Service robots: Value co-creation and co-destruction in elderly care networks. *Journal of Service Management*, *29*, 178–205.

Calic, G., & Ghasemaghaei, M. (2020). Big data for social benefits: Innovation as a mediator of the relationship between big data and corporate social performance. *Journal of Business Research*, *131*, 391-401.

Calvo, R. A., & Peters, D. (2014). *Positive Computing: Technology for Wellbeing and Human Potential*. MIT Press.

Canhoto, A. I. (2020). Leveraging machine learning in the global fight against money laundering and terrorism financing: An affordances perspective. *Journal of Business Research*, *131,* 441-452.

Capatina, A., Kachour, M., Lichy, J., Micu, A., Micu, A.-E., & Codignola, F. (2020). Matching the future capabilities of an artificial intelligence-based software for social media marketing with potential users' expectations. *Technological Forecasting and Social Change*, *151*.

Capurro, R. (2006). Towards an ontological foundation of information ethics. *Ethics and Information Technology*, *8*, 175–186.

Charness, G., Gneezy, U., & Kuhn, M. (2012). Experimental methods: Between-subject and within-subject design. *Journal of Economic Behavior & Organization*, *81*, 1–8.

Chen, C., Ibekwe-SanJuan, Fidelia, & Hou, J. (2010). The structure and dynamics of cocitation clusters: A multiple-perspective cocitation analysis *Journal of the American Society for Information Science and Technology*, *61*(7), 1386-1409.

Chen, X., Chen, J., Wu, D., Xie, Y., & Li, J. (2016). Mapping the Research Trends by Co-word Analysis Based on Keywords from Funded Project. *Procedia Computer Science*, *91*, 547–555.

Chen, Y., Mandler, T., & Meyer-Waarden, L. (2021). Three decades of research on loyalty programs: A literature review and future research agenda. *Journal of Business Research*, *124*, 179–197.

Chinchanachokchai, S., Thontirawong, P., & Chinchanachokchai, P. (2021). A tale of two recommender systems: The moderating role of consumer expertise on artificial intelligence based product recommendations. *Journal of Retailing and Consumer Services*, *61*.

Cho, H., Lee, J.-S., & Chung, S. (2010). Optimistic bias about online privacy risks: Testing the moderating effects of perceived controllability and prior experience. *Computers in Human Behavior*, *26*, 987–995.

Choi, J. K., & Ji, Y. G. (2015). Investigating the Importance of Trust on Adopting an Autonomous Vehicle. *International Journal of Human–Computer Interaction*, *31*, 692–702.

Choi, Sungwoo, Mattila, A. S., & Bolton, L. E. (2021). To Err Is Human(-oid): How Do Consumers React to Robot Service Failure and Recovery? *Journal of Service Research*, *24*, 354–371.

Choi, Sunmee, & Mattila, A. S. (2008). Perceived controllability and service expectations: Influences on customer reactions following service failure. *Journal of Business Research*, *61*(1), 24-30.

Chrysler, S., Ahmad, O., & Schwarz, C. (2015). Creating Pedestrian Crash Scenarios in a Driving Simulator Environment. *Traffic Injury Prevention*, *16 Suppl 1*, S12-7.

Chuah, S. H.-W., & Yu, J. (2021). The future of service: The power of emotion in human-robot interaction. *Journal of Retailing and Consumer Services*, *61*.

Chung, M., Ko, E., Joung, H., & Kim, S. J. (2018). Chatbot e-service and customer satisfaction regarding luxury brands. *Journal of Business Research*, *117*, 587-595.

Cloarec, J. (2020). The personalization–privacy paradox in the attention economy. *Technological Forecasting and Social Change*, *161*, 120299.

Collier, J. E. (2020). *Applied Structural Equation Modeling using AMOS: Basic to Advanced Techniques*. Routledge.

Collins, A., & Smith, E. E. (2013). *Readings in Cognitive Science: A Perspective from Psychology and Artificial Intelligence*. Elsevier.

Cooke, A. D. J., & Zubcsek, P. P. (2017). The connected consumer: Connected devices and the evolution of customer intelligence. *Journal of the Association for Consumer Research*, *2*, 164–178.

Copeland, J. (2015). *Artificial Intelligence: A Philosophical Introduction*. John Wiley & Sons.

Coughlin, S. S. (2008). How Many Principles for Public Health Ethics? *The Open Public Health Journal*, *1*, 8–16.

Culnan, M. J., & Bies, R. J. (2003). Consumer Privacy: Balancing Economic and Justice Considerations. *Journal of Social Issues*, *59*, 323–342.

Cyr, D., Head, M., Larios, H., & Pan, B. (2009). Exploring Human Images in Website Design: A Multi-Method Approach. *MIS Quarterly*, *33*, 539–566.

Dai, T., & Singh, S. (2020). Conspicuous by Its Absence: Diagnostic Expert Testing Under Uncertainty. *Marketing Science*, *39*, 540–563.

Darwin, C. (1859). *On the Origin of Species by Means of Natural Selection, or the Preservation of Favoured Races in the Struggle for Life*. International Book Company.

Davenport, T., Guha, A., Grewal, D., & Bressgott, T. (2020). How artificial intelligence will change the future of marketing. *Journal of the Academy of Marketing Science*, *48*, 24–42.

Davis, B., & Pechmann, C. (2013). Introduction to the Special Issue on transformative consumer research: Developing theory to mobilize efforts that improve consumer and societal well-being. *Journal of Business Research*, *66*, 1168–1170.

Davis, F. D. (1989). Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. *MIS Quarterly*, *13*, 319–340.

Day, G. S., & Montgomery, D. B. (1999). Charting New Directions for Marketing. *Journal of Marketing*, *63*, 3–13.

De Bellis, E., & Venkataramani Johar, G. (2020). Autonomous Shopping Systems: Identifying and Overcoming Barriers to Consumer Adoption. *Journal of Retailing*, *96*, 74–87.

De Bruyn, A., Viswanathan, V., Beh, Y. S., Brock, J. K.-U., & von Wangenheim, F. (2020). Artificial Intelligence and Marketing: Pitfalls and Opportunities. *Journal of Interactive Marketing (Elsevier)*, *51*, 91–105.

De Carlo, M., Ferilli, G., d'Angella, F., & Buscema, M. (2021). Artificial intelligence to design collaborative strategy: An application to urban destinations. *Journal of Business Research*, *129*, 936–948.

De Keyser, A., Köcher, S., Alkire (née Nasr), L., Verbeeck, C., & Kandampully, J. (2019). Frontline Service Technology infusion: Conceptual archetypes and future research directions. *Journal of Service Management*, *30*, 156–183.

De Ruyter, K., Keeling, D. I., & Yu, T. (2020). Service-Sales Ambidexterity: Evidence, Practice, and Opportunities for Future Research. *Journal of Service Research*, *23*, 13–21.

De Winter, J., Van Leeuwen, P. M., & Happee, R. (2012). Advantages and Disadvantages of Driving Simulators: A Discussion. *Proceedings of Measuring Behavior*, pp. 47–50.

Dellaert, B. G. C., Shu, S. B., Arentze, T. A., Baker, T., Diehl, K., Donkers, B., Steffel, M. (2020). Consumer decisions with artificially intelligent voice assistants. *Marketing Letters*, *31*, 335–347.

Detienne, K., & Jackson, L. (2001). Knowledge management: Understanding theory and developing strategy. *Competitiveness Review: An International Business Journal Incorporating Journal of Global Competitiveness*, *11*, 1–11.

DeWall, C. N., Finkel, E. J., & Denson, T. F. (2011). (2011). Self-control inhibits aggression. *Social and Personality Psychology Compass*, *5*, 458-472.

Dholakia, N., & Firat, A. F. (2019). Markets, consumers and society in the age of heteromation. *European Journal of Marketing*, *53*, 1504–1520.

Dholakia, N., & Reyes, I. (2018). Media, markets and violence. *Journal of Marketing Management*, *34*, 1032–1047.

Di Vaio, A., Palladino, R., Hassan, R., & Escobar, O. (2020). Artificial intelligence and business models in the sustainable development goals perspective: A systematic literature review. *Journal of Business Research*, *121*, 283–314.

Diener, Ed. (1984). Subjective well-being. *Psychological Bulletin*, *95*, 542–575.

Diener, Ed, & Chan, M. Y. (2011). Happy People Live Longer: Subjective Well-Being Contributes to Health and Longevity. *Applied Psychology: Health and Well-Being*, *3*, 1–43.

Diener, Ed, Suh, E. M., Lucas, R. E., & Smith, H. L. (1999). Subjective well-being: Three decades of progress. *Psychological Bulletin*, *125*, 276–302.

Dietvorst, B. J., Simmons, J. P., & Massey, C. (2015). Algorithm aversion: People erroneously avoid algorithms after seeing them err. *Journal of Experimental Psychology: General*, *144*, 114–126.

Dinev, T., & Hart, P. (2006). An Extended Privacy Calculus Model for E-Commerce Transactions. *Information Systems Research*, *17*, 61–80.

Donaldson, T., & Preston, L. E. (1995). The Stakeholder Theory of the Corporation: Concepts, Evidence, and Implications. *The Academy of Management Review*, *20*, 65–91.

Dorn, L., & Barker, D. (2005). The effects of driver training on simulated driving performance. *Accident Analysis & Prevention*, *37*, 63–69.

Dosovitskiy, A., Ros, G., Codevilla, F., Lopez, A., & Koltun, V. (2017). CARLA: An Open Urban Driving Simulator. *Conference on Robot Learning*, 1–16. PMLR.

Du, S., & Xie, C. (2020). Paradoxes of artificial intelligence in consumer markets: Ethical challenges and opportunities. *Journal of Business Research*, 1–14.

Dzikowski, P. (2018). A bibliometric analysis of born global firms. *Journal of Business Research*, *85*, 281–294.

Edelmann, A., Stümper, S., & Petzoldt, T. (2021). Cross-cultural differences in the acceptance of decisions of automated vehicles. *Applied Ergonomics*, *92*, 103346.

Eggers, F., & Eggers, F. (2021). Drivers of autonomous vehicles—Analyzing consumer preferences for self-driving car brand extensions. *Marketing Letters*, 1-24.

Ehret, M., & Wirtz, J. (2017). Unlocking value from machines: Business models and the industrial internet of things. *Journal of Marketing Management*, *33*, 111–130.

Epley, N. (2018). A Mind like Mine: The Exceptionally Ordinary Underpinnings of Anthropomorphism. *Journal of the Association for Consumer Research*, *3*, 591–598.

Epley, N., Waytz, A., & Cacioppo, J. T. (2007). On seeing human: A three-factor theory of anthropomorphism. *Psychological Review*, *114*, 864–886.

Epley, N., Waytz, A., Heafner, J., & Epley, N. (2018). The Mind in the Machine: Anthropomorphism Increases Trust in an Autonomous Vehicle Journal of Experimental Social Psychology The mind in the machine: Anthropomorphism increases trust in an autonomous vehicle. *Journal of Experimental Social Psychology*, *52*, 113–117.

Eppenberger, N., & Richter, M. A. (2021). The opportunity of shared autonomous vehicles to improve spatial equity in accessibility and socio-economic developments in European urban areas. *European Transport Research Review*, *13*, 32.

Ettema, D., Gärling, T., Eriksson, L., Friman, M., Olsson, L. E., & Fujii, S. (2011). Satisfaction with travel and subjective well-being: Development and test of a measurement tool. *Transportation Research Part F: Traffic Psychology and Behaviour*, *14*, 167–175.

Etzioni, A., & Etzioni, O. (2017). Incorporating Ethics into Artificial Intelligence. *Journal of Ethics*, *21*, 403–418.

European Commission. (2019). Ethics guidelines for trustworthy AI | Shaping Europe's digital future. Retrieved July 30, 2021, from https://digital-strategy.ec.europa.eu/en/library/ethics-guidelines-trustworthy-ai

Fagnant, D. J., & Kockelman, K. (2015). Preparing a nation for autonomous vehicles: Opportunities, barriers and policy recommendations. *Transportation Research Part A: Policy and Practice*, *77*, 167–181.

Fahimnia, B., Sarkis, J., & Davarzani, H. (2015). Green supply chain management: A review and bibliometric analysis. *International Journal of Production Economics*, *162*, 101–114.

Faisal, A., Kamruzzaman, M., Yigitcanlar, T., & Currie, G. (2019). Understanding autonomous vehicles: A systematic literature review on capability, impact, planning and policy. *Journal of Transport and Land Use*, *12*, 45–72.

Felzmann, H., Fosch-Villaronga, E., Lutz, C., & Tamo-Larrieux, A. (2019). Robots and Transparency: The Multiple Dimensions of Transparency in the Context of Robot Technologies. *IEEE Robotics Automation Magazine*, *26*, 71–78.

Feng, C. M., Park, A., Pitt, L., Kietzmann, J., & Northey, G. (2020). Artificial intelligence in marketing: A bibliographic perspective. *Australasian Marketing Journal*.

Fernandes, T., & Oliveira, E. (2021). Understanding consumers' acceptance of automated technologies in service encounters: Drivers of digital voice assistants adoption. *Journal of Business Research*, *122*, 180–191.

Fernandez-Rovira, C., Alvarez Valdes, J., Mollevi, G., & Nicolas-Sans, R. (2021). The digital transformation of business. Towards the datafication of the relationship with customers. *Technological Forecasting and Social Change*, *162*, 120339.

Ferreira, M.B, Costa Pinto, D., Maurer Herter, M., Soro, J., Vanneschi, L., Castelli, M., & Peres, F. (2020). Using artificial intelligence to overcome over-indebtedness and fight poverty. *Journal of Business Research*, *131,* 411-425

Fetscherin, M. (2010). The Measurement and Determinants of a Country Brand: The Country Brand Strength Index. *International Marketing Review*, *27*, 466–479.

Fiske, S. T., Cuddy, A. J. C., & Glick, P. (2007). Universal dimensions of social cognition: Warmth and competence. *Trends in Cognitive Sciences*, *11*, 77–83.

Fiske, S. T., Malone, C., & Kervyn, N. (2012). Brands as intentional agents: Our response to commentaries. *Journal of Consumer Psychology*, *22*, 205–207.

Folkes, V. S. (1984). Consumer Reactions to Product Failure: An Attributional Approach. *Journal of Consumer Research*, *10*, 398–409.

Folkman, S., & Lazarus, R. J. (1984). *Stress, Appraisal, and Coping*. Springer Publishing Company.

Folkman, S., Lazarus, R. S., Dunkel-Schetter, C., Delongis, A., & Gruen, R. J. (1986). Dynamics of a Stressful Encounter: Cognitive Appraisal, Coping, and Encounter Outcomes Susan. *Journal of Personality and Social Psychology*, *50*, 992–1003.

Foot, P. (1967). Problem of Abortion and the Doctrine of the Double Effect, *Oxford Review,* 5

Forrester. (2019). Customer Service Chatbots Fail Consumers Today. Retrieved August 12, 2021, from Forrester website: https://www.forrester.com/report/Forrester+Infographic+Customer+Service+Chatbots+Fail+Consumers+Today/RES144755

Foss. (2007). The Entrepreneurial Organization of Heterogeneous Capital. *Journal of Management Studies*, *44(7)*, 1165-1186.

Fossen, F. M., & Sorgner, A. (2021). Digitalization of work and entry into entrepreneurship. *Journal of Business Research*, *125*, 548–563.

Fournier, S., & Alvarez, C. (2012). Brands as relationship partners: Warmth, competence, and in-between. *Journal of Consumer Psychology*, *22*, 177–185.

Frow, P., McColl-Kennedy, J. R., Payne, A., & Govind, R. (2019a). Service ecosystem well-being: Conceptualization and implications for theory and practice. *European Journal of Marketing*, *53*, 2657–2691.

Frow, P., McColl-Kennedy, J. R., Payne, A., & Govind, R. (2019b). Service ecosystem well-being: Conceptualization and implications for theory and practice. *European Journal of Marketing*, *53*, 2657–2691.

Gabbott, M., Tsarenko, Y., & Mok, W. H. (2011). Emotional intelligence as a moderator of coping strategies and service outcomes in circumstances of service failure. *Journal of Service Research*, *14*, 234–248.

Gaggioli, A., Villani, D., Serino, S., Banos, R., & Botella, C. (2019). Editorial: Positive Technology: Designing E-experiences for Positive Change. *Frontiers in Psychology*, *10*, 1571.

Gallegati, M. (2018). *Complex Agent-Based Models*. Springer International Publishing.

Gallup, G. (1988). Survey Research: Current Problems and Future Opportunities. *Journal of Consumer Marketing*, *5*, 27–30.

Gäthke, J. (2020). The impact of augmented reality on overall service satisfaction in elaborate servicescapes. *Journal of Service Management*, *31*, 227–246.

Gefen, D., Karahanna, E., & Straub, D. W. (2003). Trust and Tam in online shopping: An integrated model. *MIS Quarterly*, *27*, 51–90.

Gelbrich, K. (2010). Anger, frustration, and helplessness after service failure: Coping strategies and effective informational support. *Journal of the Academy of Marketing Science*, *38*, 567–585.

Gelbrich, K., Hagel, J., & Orsingher, C. (2021). Emotional support from a digital assistant in technology-mediated services: Effects on customer satisfaction and behavioral persistence. *International Journal of Research in Marketing*, *38*, 176–193.

Gerbner, G., & Gross, L. (1976). Living with Television: The Violence Profile. *Journal of Communication*, *26*, 172–199.

Geurs, K. T., & van Wee, B. (2004). Accessibility evaluation of land-use and transport strategies: Review and research directions. *Journal of Transport Geography*, *12*, 127–140.

Gibson, J. J. (1979). *The theory of affordances.1(2),*. USA: Hilldale.

Giebelhausen, M., Robinson, S. G., Sirianni, N. J., & Brady, M. K. (2014). Touch versus tech: When technology functions as a barrier or a benefit to service encounters.*Journal of Marketing,*78(4), 113-124.

Glikson, E., & Woolley, A. W. (2020). Human Trust in Artificial Intelligence: Review of Empirical Research. *Academy of Management Annals*, *14*, 627–660.

Glushko, R. J., & Nomorosa, K. J. (2013). Substituting Information for Interaction: A Framework for Personalization in Service Encounters and Service Systems. *Journal of Service Research*, *16*, 21–38.

Gneezy, A. (2017). Field Experimentation in Marketing Research. *Journal of Marketing Research*, *54*, 140–143.

Go, E., & Sundar, S. S. (2019a). Humanizing chatbots: The effects of visual, identity and conversational cues on humanness perceptions. *Computers in Human Behavior*, *97*, 304–316.

Go, E., & Sundar, S. S. (2019b). Humanizing chatbots: The effects of visual, identity and conversational cues on humanness perceptions. *Computers in Human Behavior*, *97*, 304–316.

Goldsmith, J., & Burton, E. (2017). Why Teaching Ethics to AI Practitioners is Important.

Workshops at the Thirty-First AAAI Conference on Artificial Intelligence.

Golossenko, A., Pillai, K. G., & Aroean, L. (2020). Seeing brands as humans: Development and validation of a brand anthropomorphism scale. *International Journal of Research in Marketing*, *37*, 737–755.

Gozman, D., & Willcocks, L. (2019). The emerging Cloud Dilemma: Balancing innovation with cross-border privacy and outsourcing regulations. *Journal of Business Research*, *97*, 235–256.

Grandey, A. A. (2003). When "The Show Must Go On": Surface Acting and Deep Acting as Determinants of Emotional Exhaustion and Peer-Rated Service Delivery. *Academy of Management Journal*, *46*, 86–96.

Granulo, A., Fuchs, C., & Puntoni, S. (2021). Preference for Human (vs. Robotic) Labor is Stronger in Symbolic Consumption Contexts. *Journal of Consumer Psychology*, *31*, 72–80.

Gray, K., & Wegner, D. M. (2012). Feeling robots and human zombies: Mind perception and the uncanny valley. *Cognition*, *125*, 125–130.

Gray, K., Young, L., & Waytz, A. (2012). Mind Perception Is the Essence of Morality. *Psychological Inquiry*, *23*, 101–124.

Grégoire, Y., & Fisher, R. J. (2008). Customer betrayal and retaliation: When your best customers become your worst enemies. *Journal of the Academy of Marketing Science*, *36*, 247–261.

Grewal, D., Roggeveen, A. L., & Nordfält, J. (2017). The Future of Retailing. *Journal of Retailing*, *93*, 1–6.

Grewal, Dhruv, Hulland, J., Kopalle, P. K., & Karahanna, E. (2020). The future of technology and marketing: A multidisciplinary perspective. *Journal of the Academy of Marketing Science*, *48*, 1–8.

Gronroos, C. (1988). Service Quality: The Six Criteria Of Good Perceived Service. *Review of business*, *9*, 10.

Grönroos, C., & Voima, P. (2013). Critical service logic: Making sense of value creation and co-creation. *Journal of the Academy of Marketing Science*, *41*, 133–150.

Guha, A., Grewal, D., Kopalle, P. K., Haenlein, M., Schneider, M. J., Jung, H., … Hawkins, G. (2021). How artificial intelligence will affect the future of retailing. *Journal of Retailing*, *97*, 28–41.

Gupta, S., Leszkiewicz, A., Kumar, V., Bijmolt, T., & Potapov, D. (2020). Digital Analytics: Modeling for Insights and New Methods. *Journal of Interactive Marketing (Elsevier)*, *51*, 26–43.

Gurumurthy, K. M., & Kockelman, K. M. (2020). Modeling Americans' autonomous vehicle preferences: A focus on dynamic ride-sharing, privacy & long-distance mode choices. *Technological Forecasting and Social Change*, *150*, 119792.

Gwinner, K. P., Bitner, M. J., Brown, S. W., & Kumar, A. (2005). Service Customization Through Employee Adaptiveness. *Journal of Service Research*, *8*, 131–148.

Haenlein, M., & Kaplan, A. (2019). A Brief History of Artificial Intelligence: On the Past, Present, and Future of Artificial Intelligence. *California management review, 61*(4), 5-14.

Haenlein, M., & Kaplan, A. (2021). Artificial intelligence and robotics: Shaking up the business world and society at large. *Journal of Business Research*, *124*, 405–407.

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2013). *Multivariate Data Analysis*. Pearson Education Limited.

Hamilton, R., Ferraro, R., Haws, K. L., & Mukhopadhyay, A. (2021). Traveling with Companions: The Social Customer Journey. *Journal of Marketing*, *85*, 68–92.

Harper, C. D., Hendrickson, C. T., Mangones, S., & Samaras, C. (2016). Estimating potential increases in travel with autonomous vehicles for the non-driving, elderly and people with travel-restrictive medical conditions. *Transportation Research Part C: Emerging Technologies*, *72*, 1–9.

Harrell, E. (2019). Neuromarketing: What You Need to Know. *Harvard Business Review*. *97*(4), 64-70.

Hartline, M. D., & Ferrell, O. C. (1996). The Management of Customer-Contact Service Employees: An Empirical Investigation. *Journal of Marketing*, *60*, 52–70.

Hartwich, F., Beggiato, M., & Krems, J. F. (2018). Driving comfort, enjoyment and acceptance of automated driving – effects of drivers' age and driving style familiarity. *Ergonomics*, *61*, 1017–1032.

Hasan, R., Shams, R., & Rahman, M. (2020). Consumer trust and perceived risk for voice-controlled artificial intelligence: The case of Siri. *Journal of Business Research*, *131,* 591-597

Haslam, N., & Loughnan, S. (2014). Dehumanization and Infrahumanization. *Annual Review of Psychology*, *65*, 399–423.

Hatfield, E., Bensman, L., Thornton, P. D., & Rapson, R. L. (2014). New Perspectives on Emotional Contagion: A Review of Classic and Recent Research on Facial Mimicry and Contagion.

Hayes, A. F. (2018). Partial, conditional, and moderated moderated mediation: Quantification, inference, and interpretation. *Communication monographs*, *85*(1), 4-40.

Hecht, J. (2018). Managing expectations of artificial intelligence. *Nature*, *563*, S141–S143.

Helliwell, J. F., & Huang, H. (2011). Well-Being and Trust in the Workplace. *Journal of Happiness Studies*, *12*, 747–767.

Hengstler, M., Enkel, E., & Duelli, S. (2016). Applied artificial intelligence and trust-The case of autonomous vehicles and medical assistance devices. *Technological Forecasting and Social Change*, *105*, 105–120.

Henkel, A. P., Bromuri, S., Iren, D., & Urovi, V. (2020). Half human, half machine – augmenting service employees with AI for interpersonal emotion regulation. *Journal of Service Management*, *31*, 247–265.

Hennig-Thurau, T., Gwinner, K. P., Walsh, G., & Gremler, D. D. (2004). Electronic word-of-mouth via consumer-opinion platforms: What motivates consumers to articulate themselves on the Internet? *Journal of Interactive Marketing*, *18*, 38–52.

Hennig-Thurau, T., Hofacker, C., & Bloching, B. (2013). Marketing the Pinball Way: Understanding How Social Media Change the Generation of Value for Consumers and Companies. *Journal of Interactive Marketing*, *27*, 237–241.

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, *43*, 115–135.

Hermann, E. (2021). Leveraging Artificial Intelligence in Marketing for Social Good—An Ethical Perspective. *Journal of Business Ethics*, 1-19

Hess, R. L., Ganesan, S., & Klein, N. M. (2003). Service failure and recovery: The impact of relationship factors on customer satisfaction. *Journal of the Academy of Marketing Science*, *31*, 127–145.

Higgins, N. C., Amand, M. D. S., & Poole, G. D. (n.d.). *The Controllability of Negative Life Experiences Mediates Unrealistic Optimism*. 25.

Hildebrand, C., Efthymiou, F., Busquet, F., Hampton, W. H., Hoffman, D. L., & Novak, T. P. (2020). Voice analytics in business research: Conceptual foundations, acoustic feature extraction, and applications. *Journal of Business Research*, *121*, 364–374.

Hock, P., Kraus, J., Babel, F., Walch, M., Rukzio, E., & Baumann, M. (2018). How to Design Valid Simulator Studies for Investigating User Experience in Automated Driving: Review and Hands-On Considerations In *Proceedings of the 10th International Conference on Automotive User Interfaces and Interactive Vehicular Applications,* 105-117.

Hoffman, D. L., & Novak, T. P. (2018). Consumer and Object Experience in the Internet of Things: An Assemblage Theory Approach. *Journal of Consumer Research*, p. 44(6), 1178–1204.

Hohenberger, C., Spörrle, M., & Welpe, I. M. (2017). Not fearless, but self-enhanced: The effects of anxiety on the willingness to use autonomous cars depend on individual levels of self-enhancement. *Technological Forecasting and Social Change*, *116*, 40–52.

Hollebeek, L. D., Clark, M. K., & Macky, K. (2020). Demystifying consumer digital cocreated value: Social presence theory-informed framework and propositions. *Recherche et Applications En Marketing*.

Hollebeek, L. D., Sprott, D. E., & Brady, M. K. (2021). Rise of the Machines? Customer Engagement in Automated Service Interactions. *Journal of Service Research*, *24*, 3–8.

Horton, D., & Wohl, R. R. (1956). Mass Communication and Para-Social Interaction. *Psychiatry*, *19*, 215–229.

Hoyer, W. D., Kroschke, M., Schmitt, B., Kraume, K., & Shankar, V. (2020). Transforming the Customer Experience Through New Technologies. *Journal of Interactive Marketing (Elsevier)*, *51*, 57–71.

Huang, J. (2007). Extracting Chatbot Knowledge from Online Discussion Forums. *IJCAI International Joint Conference on Artificial Intelligence*, *II*, 423–428.

Huang, M.-H., & Rust, R. T. (2018). Artificial Intelligence in Service. *Journal of Service Research*, *21*, 155–172.

Huang, M.-H., & Rust, R. T. (2021a). Engaged to a Robot? The Role of AI in Service. *Journal of Service Research*, *24*, 30–41.

Huang, M.-H., & Rust, R. T. (2021b). A Framework for Collaborative Artificial Intelligence in Marketing. *Journal of Retailing*.

Huang, Ming-Hui, & Rust, R. T. (2021c). A strategic framework for artificial intelligence in marketing. *Journal of the Academy of Marketing Science*, *49*, 30–50.

Huang, Y., & Qian, L. (2021). Understanding the potential adoption of autonomous vehicles in China: The perspective of behavioral reasoning theory. *Psychology and Marketing*, *38*, 669–690.

Hult, G. T. M., Walkowiak, T. A., & Beck, J. M. (2020). Service research: Progress toward interdisciplinary collaboration. *Journal of Services Marketing*, *34*, 363–371.

Humphreys, A., & Wang, R. (2018). Automated Text Analysis for Consumer Research. *Journal of Consumer Research*, *44*, 1274–1306.

Hursthouse, R. (1999). *On Virtue Ethics*. OUP Oxford.

Huta, V., & Ryan, R. M. (2010). Pursuing pleasure or virtue: The differential and overlapping well-being benefits of hedonic and eudaimonic motives. *Journal of Happiness Studies: An Interdisciplinary Forum on Subjective Well-Being*, *11*, 735–762.

Jelodar, H., Wang, Y., Yuan, C., Feng, X., Jiang, X., Li, Y., & Zhao, L. (2019). Latent Dirichlet allocation (LDA) and topic modeling: Models, applications, a survey. *Multimedia Tools and Applications*, *78*, 15169–15211.

Jha, K., Doshi, A., Patel, P., & Shah, M. (2019). A comprehensive review on automation in agriculture using artificial intelligence. *Artificial Intelligence in Agriculture*, *2*, 1–12.

Jobin, A., Ienca, M., & Vayena, E. (2019). The global landscape of AI ethics guidelines. *Nature Machine Intelligence*, *1*, 389–399.

Jörling, M., Böhm, R., & Paluch, S. (2019). Service Robots: Drivers of Perceived Responsibility for Service Outcomes. *Journal of Service Research*, *22*, 404–420.

Judd, C. M., Kenny, D. A., & McClelland, G. H. (2001). Estimating and testing mediation and moderation in within-subject designs. *Psychological Methods*, *6*, 115–134.

Kahneman, D., & Tversky, A. (2014). Choices, Values, and Frames. In *Handbook of the Fundamentals of Financial Decision Making*, *Part I*, 269-278

Kaiser, C., Ahuvia, A., Rauschnabel, P. A., & Wimble, M. (2020). Social media monitoring: What can marketers learn from Facebook brand photos? *Journal of Business Research*, *117*, 707–717.

Kalamas, M., Laroche, M., & Makdessian, L. (2008). Reaching the boiling point: Consumers' negative affective reactions to firm-attributed service failures. *Journal of Business Research*, *61*, 813–824.

Kant, I. (1788). Critique of Practical Reason, *Cambridge University Press*.

Kaplan, A., & Haenlein, M. (2019). Siri, Siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence. *Business Horizons*, *62*, 15–25.

Karimova, G. Z., & Goby, V. P. (2021). The adaptation of anthropomorphism and archetypes for marketing artificial intelligence. *Journal of Consumer Marketing*, *38*, 229–238.

Kashyap, R. (2021). Artificial Intelligence: A Child's Play. *Technological Forecasting and Social Change*, *166*, 1-54.

Kaur, K., & Rampersad, G. (2018). Trust in driverless cars: Investigating key factors influencing the adoption of driverless cars. *Journal of Engineering and Technology Management*, *48*, 87–96.

Kempf, D. S. (1999). Attitude formation from product trial: Distinct roles of cognition and affect for hedonic and functional products. *Psychology & Marketing*, *16*, 35–50.

Kennedy, R. S., Lane, N. E., Berbaum, K. S., & Lilienthal, M. G. (1993). Simulator Sickness Questionnaire: An Enhanced Method for Quantifying Simulator Sickness. *The International Journal of Aviation Psychology*, *3*, 203–220.

Key, Thomas Martin, & Keel, A. L. (2020). How executives talk: Exploring marketing executive value articulation with computerized text analysis. *European Journal of Marketing*, *54*, 546–569.

Key, T.M., & Keel, A. L. (2020). How executives talk: Exploring marketing executive value articulation with computerized text analysis. *European Journal of Marketing*, *54*, 546–569.

Khastgir, S., Birrell, S., Dhadyalla, G., & Jennings, P. (2018). Calibrating trust through knowledge: Introducing the concept of informed safety for automation in vehicles. *Transportation Research Part C: Emerging Technologies*, *96*, 290–303.

Kietzmann, J., & Pitt, L. F. (2020). Computerized content analysis of online data – opportunities for marketing scholars and practitioners. *European Journal of Marketing*, *54*, 473–477.

Kim, M. J., & Hall, C. M. (2019). A hedonic motivation model in virtual reality tourism: Comparing visitors and non-visitors. *International Journal of Information Management*, *46*, 236–249.

Kim, S., Chen, R. P., & Zhang, K. (2016). Anthropomorphized helpers undermine autonomy and enjoyment in computer games. *Journal of Consumer Research*, *43*, 282–302.

Kim, S., & McGill, A. L. (2011). Gaming with Mr. Slot or Gaming the Slot Machine? Power, Anthropomorphism, and Risk Perception. *Journal of Consumer Research*, *38*, 94–107.

Kim, S. Y., Schmitt, B. H., & Thalmann, N. M. (2019). Eliza in the uncanny valley: Anthropomorphizing consumer robots increases their perceived warmth but decreases liking. *Marketing Letters*, *30*, 1–12.

Klaus, P., & Zaichkowsky, J. (2020). AI voice bots: A services marketing research agenda. *Journal of Services Marketing*, *34*, 389–398.

Köhler, C. F., Rohm, A. J., De Ruyter, K., & Wetzels, M. (2011). Return on interactivity: The impact of online agents on newcomer adjustment. *Journal of Marketing*, *75*, 93–108.

Kolbjørnsrud, V., Amico, R., & Thomas, R. J. (2016). *How Artificial Intelligence Will Redefine Management*. *Harvard Business Review, 2*, 1-6.

König, M., & Neumayr, L. (2017). Users' resistance towards radical innovations: The case of the self-driving car. *Transportation Research Part F: Traffic Psychology and Behaviour*, *44*, 42–52.

Kot, M. T., & Leszczyński, G. (2020). The concept of intelligent agent in business interactions: Is virtual assistant an actor or a boundary object? *Journal of Business and Industrial Marketing*, *35*, 1155–1164.

Kozinets, R. V., & Gretzel, U. (2021). Commentary: Artificial Intelligence: The Marketer's Dilemma. *Journal of Marketing*, *85*, 156–159.

Krabuanrat, K., & Phelps, R. (1998). Heuristics and rationality in strategic decision making: An exploratory study. *Journal of Business Research*, *41*, 83–93.

Krafft, M., Sajtos, L., & Haenlein, M. (2020). Challenges and Opportunities for Marketing Scholars in Times of the Fourth Industrial Revolution. *Journal of Interactive Marketing (Elsevier)*, *51*, 1–8.

Kramer, R. M., & Cook, K. S. (2004). *Trust and Distrust In Organizations: Dilemmas and Approaches*. Russell Sage Foundation.

Kruger, J., & Dunning, D. (1999). Unskilled and unaware of it: How difficulties in recognizing one's own incompetence lead to inflated self-assessments. *Journal of Personality and Social Psychology*, *77*, 1121–1134.

Kuhn, M., & Marquardt, V. (2019). "What-are-you-looking-at?" – Implicit Behavioural Measurement Indicating Technology Acceptance in the Field of Automated Driving. *Academy of Marketing Science Annual Conference*, 595–606.

Kulviwat, S., Ii, G. C. B., Kumar, A., Nasco, S. A., & Clark, T. (2007). Toward a unified theory of consumer acceptance technology. *Psychology & Marketing*, *24*, 1059–1084.

Kumar, V., Ramachandran, D., & Kumar, B. (2021). Influence of new-age technologies on marketing: A research agenda. *Journal of Business Research*, *125*, 864–877.

Lalicic, L., & Weismayer, C. (2021). Consumers' reasons and perceived value co-creation of using artificial intelligence-enabled travel service agents. *Journal of Business Research*, *129*, 891–901.

Langley, D. J., van Doorn, J., Ng, I. C. L., Stieglitz, S., Lazovik, A., & Boonstra, A. (2021). The Internet of Everything: Smart things and their impact on business models. *Journal of Business Research*, *122*, 853–863.

Lazarus, R. S. (1991). Emotion and adaptation. In *Oxford University Press*. New York, NY.

Lee, E. (2010). The more humanlike, the better? How speech type and users' cognitive style affect social responses to computers. *Computers in Human Behavior*, *26*, 665–672.

Lee, J., & Moray, N. (1992). Trust, control strategies and allocation of function in human-machine systems. *Ergonomics*, *35*, 1243–1270.

Lee, J., & See, K. (2004). Trust in Automation: Designing for Appropriate Reliance. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, *46(1)*, 50-80.

Lee, Linda W., Dabirian, A., McCarthy, I. P., & Kietzmann, J. (2020). Making sense of text: Artificial intelligence-enabled content analysis. *European Journal of Marketing*, *54*, 615–644.

Lee, M. K. (2018). Understanding perception of algorithmic decisions: Fairness, trust , and emotion in response to algorithmic management. *Big Data & Society*, *5*, 1–16.

Lemon, K. N., & Verhoef, P. C. (2016). Understanding Customer Experience Throughout the Customer Journey -. *Journal of Marketing. 80(6)*, 69-96.

Leo, X., & Huh, Y. E. (2020). Who gets the blame for service failures? Attribution of responsibility toward robot versus human service providers and service firms. *Computers in Human Behavior*, *113*, 106520.

Leone, D., Schiavone, F., Appio, F. P., & Chiao, B. (2021). How does artificial intelligence enable and enhance value co-creation in industrial markets? An exploratory case study in the healthcare ecosystem. *Journal of Business Research*, *129*, 849–859.

Lester, J., Branting, K., & Mott, B. (2004). Conversational Agents. *The Practical Handbook of Internet Computing*, 220-240.

Letheren, K., Russell-Bennett, R., & Whittaker, L. (2020). Black, white or grey magic? Our future with artificial intelligence. *Journal of Marketing Management*, *36*, 216–232.

Li, H. (Alice), & Kannan, P. K. (2014). Attributing Conversions in a Multichannel Online Marketing Environment: An Empirical Model and a Field Experiment. *Journal of Marketing Research*, *51*, 40–56.

Li, J., Zhao, X., Cho, M.-J., Ju, W., & Malle, B. F. (2016, April 5). *From Trolley to Autonomous Vehicle: Perceptions of Responsibility and Moral Norms in Traffic Accidents with Self-Driving Cars*. 2016-01–0164.

Liang, H., Xue, Y., Pinsonneault, A., & Wu, Y. (2019). What Users Do Besides Problem-Focused Coping When Facing IT Security Threats: An Emotion-Focused Coping Perspective. *Management Information Systems Quarterly*, *43*, 373–394.

Libai, B., Bart, Y., Gensler, S., Hofacker, C. F., Kaplan, A., Kötterheinrich, K., & Kroll, E. B. (2020). Brave New World? On AI and the Management of Customer Relationships. *Journal of Interactive Marketing (Elsevier)*, *51*, 44–56.

Liu, B., & Sundar, S. S. (2018). Should Machines Express Sympathy and Empathy? Experiments with a Health Advice Chatbot. *Cyberpsychology, Behavior, and Social Networking, 21*, 625–636.

Liu, H.Y. (2017). Irresponsibilities, inequalities and injustice for autonomous vehicles. *Ethics and Information Technology*, *19*, 193–207.

Longoni, C., Bonezzi, A., & Morewedge, C. K. (2019). Resistance to Medical Artificial Intelligence. *Journal of Consumer Research*, *46*, 629–650.

Longoni, C., & Cian, L. (2020). Artificial Intelligence in Utilitarian vs. Hedonic Contexts: The “Word-of-Machine” Effect. *Journal of Marketing*.

López-Duarte, C., Vidal-Suárez, M., & González-Díaz, B. (2016). International Business and National Culture: A Literature Review and Research Agenda. *International Journal of Management Reviews*, *18*.

Loureiro, S. M. C., Guerreiro, J., & Tussyadiah, I. (2020). Artificial intelligence in business: State of the art and future research agenda. *Journal of Business Research*, *129*, 911-926.

Lu, Y., Papagiannidis, S., & Alamanos, E. (2019). Exploring the emotional antecedents and outcomes of technology acceptance. *Computers in Human Behavior*, *90*, 153–169.

Lu, Y., Papagiannidis, S., & Alamanos, E. (2021). Adding ‘things’ to the internet: Exploring the spillover effect of technology acceptance. *Journal of Marketing Management*, *37*, 626–650.

Lucas, K., van Wee, B., & Maat, K. (2016). A method to evaluate equitable accessibility: Combining ethical theories and accessibility-based approaches. *Transportation*, *43*, 473–490.

Lucas, R. E. (1978). On the Size Distribution of Business Firms. *The Bell Journal of Economics*, *9*, 508–523.

Luo, X., Qin, M. S., Fang, Z., & Qu, Z. (2021). Artificial Intelligence Coaches for Sales Agents: Caveats and Solutions. *Journal of Marketing*, *85*, 14–32.

Luo, Xueming. (2002). Trust production and privacy concerns on the Internet: A framework based on relationship marketing and social exchange theory. *Industrial Marketing Management*, *31*, 111–118.

Luo, Xueming, Tong, S., Fang, Z., & Qu, Z. (2019). Frontiers: Machines vs. Humans: The Impact of Artificial Intelligence Chatbot Disclosure on Customer Purchases. *Marketing Science*, *38*, 937–947.

Lusch, R. F., & Vargo, S. L. (2014). *The Service-Dominant Logic of Marketing: Dialog, Debate, and Directions*. Routledge.

Ma, L., & Sun, B. (2020). Machine learning and AI in marketing – Connecting computing power to human insights. *International Journal of Research in Marketing*, *37*, 481–504.

Ma, X., Ma, Z., Zhu, X., Cao, J., & Yu, F. (2019). Driver Behavior Classification under Cut-In Scenarios Using Support Vector Machine Based on Naturalistic Driving Data (SAE Technical Paper No. 2019-01–0136). Warrendale, PA: SAE International.

Maass, W., Parsons, J., Purao, S., Storey, V., & Woo, C. (2018). Data-Driven Meets Theory-Driven Research in the Era of Big Data: Opportunities and Challenges for Information Systems Research. *Journal of the Association for Information Systems*, *19 (12), 1.*

MacInnis, D. J., & Folkes, V. S. (2017). Humanizing brands: When brands seem to be like me, part of me, and in a relationship with me. *Journal of Consumer Psychology*, *27*, 355–374.

Makarius, E. E., Mukherjee, D., Fox, J. D., & Fox, A. K. (2020). Rising with the machines: A sociotechnical framework for bringing artificial intelligence into the organization. *Journal of Business Research*, *120*, 262–273.

Malhotra, N. K., Kim, S. S., & Agarwal, J. (2004). Internet Users' Information Privacy Concerns (IUIPC): The Construct, the Scale, and a Causal Model. *Information Systems Research*, *15*, 336–355.

Manser Payne, E. H., Dahl, A. J., & Peltier, J. (2021). Digital servitization value co-creation framework for AI services: A research agenda for digital transformation in financial service ecosystems. *Journal of Research in Interactive Marketing*.

Manser Payne, E. H., Peltier, J., & Barger, V. A. (2021). Enhancing the value co-creation process: Artificial intelligence and mobile banking service platforms. *Journal of Research in Interactive Marketing*.

Marchand, A., & Marx, P. (2020). Automated Product Recommendations with Preference-Based Explanations. *Journal of Retailing*, *96*, 328–343.

Marinova, D., de Ruyter, K., Huang, M.-H., Meuter, M. L., & Challagalla, G. (2017). Getting Smart: Learning From Technology-Empowered Frontline Interactions. *Journal of Service Research*, *20*, 29–42.

Martin, K. D., & Murphy, P. E. (2017a). The role of data privacy in marketing. *Journal of the Academy of Marketing Science*, *45*, 135–155.

Martin, K. D., & Murphy, P. E. (2017b). The role of data privacy in marketing. *Journal of the Academy of Marketing Science*, *45*, 135–155.

Martínez-Caro, E., Cegarra-Navarro, J. G., García-Pérez, A., & Fait, M. (2018). Healthcare service evolution towards the Internet of Things: An end-user perspective. *Technological Forecasting and Social Change*, *136*, 268–276.

Martínez-López, F., & Casillas, J. (2013). Artificial intelligence-based systems applied in industrial marketing: An historical overview, current and future insights. *Industrial Marketing Management*,*42*(4), 489-495.

Martins, S. M., Ferreira, F. A. F., Ferreira, J. J. M., & Marques, C. S. E. (2020). An artificial-intelligence-based method for assessing service quality: Insights from the prosthodontics sector. *Journal of Service Management*, *31*, 291–312.

Matz, S., & Netzer, O. (2017). Using Big Data as a window into consumers' psychology. *Current Opinion in Behavioral Sciences*, *18*, 7–12.

Mayer, R. C., Davis, J. H., & Schoorman, F. D. (1995a). An Integrative Model of Organizational Trust. *The Academy of Management Review*, *20*, 709–734.

McCarthy, E. J. (1960). *Basic marketing,a managerial approach.* Homewood.

McCollough, M. A., Berry, L. L., & Yadav, M. S. (2000). An Empirical Investigation of Customer Satisfaction after Service Failure and Recovery. *Journal of Service Research*, *3*, 121–137.

McCulloch, W. S., & Pitts, W. (1943). A logical calculus of the ideas immanent in nervous activity. *The Bulletin of Mathematical Biophysics*, *5*, 115–133.

McGehee, D. V., Lee, J. D., Rizzo, M., & Bateman, K. (2001). Examination of Older Driver Steering Adaptation on a High Performance Driving Simulator. *Proceedings of the First International Driving Symposium on Human Factors in Driver Assessment,* *Training and Vehicle Design: Driving Assessment 2001*, 197–201. Aspen, Colorado, USA: University of Iowa.

McIntyre, S. H., Achabal, D. D., & Miller, C. M. (1993). Applying case-based reasoning to forecasting retail sales. *Journal of Retailing*, *69*, 372–398.

Mcknight, D. (2005). Trust in Information Technology. *The Blackwell encyclopedia of management, 7*, 329-331.

Mcknight, D. H., Carter, M., Thatcher, J. B., & Clay, P. F. (2011). Trust in a specific technology: An investigation of its components and measures. *ACM Transactions on Management Information Systems*, *2*, 1–25.

McKnight, D. H., Choudhury, V., & Kacmar, C. (2002). The impact of initial consumer trust on intentions to transact with a web site: A trust building model. *Journal of Strategic Information Systems*, *11*, 297–323.

McKnight, H. D., & Chervany, N. L. (2001). Trust and Distrust Definitions: One Bite at a Time. In R. Falcone, M. Singh, & Y.-H. Tan (Eds.), *Trust in Cyber-societies* (pp. 27–54). Berlin, Heidelberg: Springer.

McLean, G., Osei-Frimpong, K., & Barhorst, J. (2021). Alexa, do voice assistants influence consumer brand engagement? – Examining the role of AI powered voice assistants in influencing consumer brand engagement. *Journal of Business Research*, *124*, 312–328.

Meade, A. W., & Craig, S. B. (2012). Identifying careless responses in survey data. *Psychological Methods*, *17*, 437–455.

Mehrabian, A., & Russell, J. A. (1974). *An approach to environmental psychology* (the MIT Press, pp. xii, 266). Cambridge, MA, US: The MIT Press.

Mele, C., Russo Spena, T., Kaartemo, V., & Marzullo, M. L. (2021). Smart nudging: How cognitive technologies enable choice architectures for value co-creation. *Journal of Business Research*, *129*, 949–960.

Mende, M., Scott, M. L., 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*, 535–556.

Menon, N., Zhang, Y., Pinjari, A. R., & Mannering, F. (2020). A statistical analysis of consumer perceptions towards automated vehicles and their intended adoption. *Transportation Planning and Technology*, *43*, 253–278.

Meuter, M. L., Ostrom, A. L., Roundtree, R. I., Bitner, M. J., Meuter, M. L., Ostrom, A. L., Bitner, M. J. (2018). *Self-Service Technologies: Satisfaction with Technology-Based Service Encounters*. *64*, 50–64.

Meyer, C., Cohen, D., & Nair, S. (2020). From automats to algorithms: The automation of services using artificial intelligence. *Journal of Service Management*, *31*, 145–161.

Meyer-Waarden, L., & Cloarec, J. (2021). “Baby, you can drive my car”: Psychological antecedents that drive consumers’ adoption of AI-powered autonomous vehicles. *Technovation,* 102348.

Meyer-Waarden, L., Pavone, G., Poocharoentou, T., Prayatsup, P., Ratinaud, M., Tison, A., & Torné, S. (2020). How Service Quality Influences Customer Acceptance and Usage of Chatbots? *Journal of Service Management Research*, *4*, 35–51.

Michalos, A. C. (1990). The impact of trust on business, international security and the quality of life. *Journal of Business Ethics*, *9*, 619–638.

Mick, D. G., & Fournier, S. (1998). Paradoxes of Technology: Consumer Cognizance, Emotions, and Coping Strategies. *Journal of Consumer Research*, *25*, 123–143.

Mill, J. S. (1861). *Utilitarianism*. London : Parker, Son, and Bourn.

MIT Technology Review Insights. (2020). *The global AI agenda: North America. MIT Technology Review*. available at https://mittrinsights.s3.amazonaws.com/AIagenda2020/NAAIagenda.pdf, accessed on 10/08/2020.

Mitchell, A. A., Russo, J. E., & Wittink, D. R. (1991). Issues in the development and use of expert systems for marketing decisions. *International Journal of Research in Marketing*, *8*, 41–50.

Mithas, S., Hofacker, C. F., Bilgihan, A., Dogru, T., Bogicevic, V., & Sharma, A. (2020). Information technology and Baumol's cost disease in healthcare services: A research agenda. *Journal of Service Management*, *31*, 911–937.

Modigliani, F. (1966). The life cycle hypothesis of saving, the demand for wealth and the supply of capital. *Social Research*, *33*, 160–217.

Montoya, A. K., & Hayes, A. F. (2017). Two-condition within-participant statistical mediation analysis: A path-analytic framework. *Psychological Methods*, *22*, 6–27.

Morgan, R. M., & Hunt, S. D. (1994). The Commitment-Trust Theory of Relationship Marketing. *Journal of Marketing*, *58*, 20–38.

Mori, M. (1970). Bukimi no tani [the uncanny valley]. *Energy*, *7*, 33–35.

Moriuchi, E., Landers, V. M., Colton, D., & Hair, N. (2020). Engagement with chatbots versus augmented reality interactive technology in e-commerce. *Journal of Strategic Marketing*, *29*(5), 375-389

Moriuchi, E. (2019). Okay, Google!: An empirical study on voice assistants on consumer engagement and loyalty. *Psychology & Marketing*, *36*, 489–501.

Moriuchi, Emi. (2021). An empirical study on anthropomorphism and engagement with disembodied AIs and consumers' re-use behavior. *Psychology & Marketing*, *38*, 21–42.

Muir, B. M. (1994). Trust in automation: Part I. Theoretical issues in the study of trust and human intervention in automated systems. *Ergonomics*, *37*, 1905–1922.

Muller, E., & Peres, R. (2019). The effect of social networks structure on innovation performance: A review and directions for research. *International Journal of Research in Marketing*, *36*, 3–19.

Munzel, A., Meyer-Waarden, L., & Galan, J.-P. (2018). The social side of sustainability: Well-being as a driver and an outcome of social relationships and interactions on social networking sites. *Technological Forecasting and Social Change*, *130*, 14–27.

Muraven, M., & Slessareva, E. (2003). Mechanisms of Self-Control Failure: Motivation and Limited Resources. *Personality and Social Psychology Bulletin*, *29*, 894–906.

Murtarelli, G., Gregory, A., & Romenti, S. (2021). A conversation-based perspective for shaping ethical human–machine interactions: The particular challenge of chatbots. *Journal of Business Research*, *129*, 927–935.

Mustak, M., Salminen, J., Plé, L., & Wirtz, J. (2021). Artificial intelligence in marketing: Topic modeling, scientometric analysis, and research agenda. *Journal of Business Research*, *124*, 389–404.

Nass, C., & Lee, K. M. (2001). Does computer-synthesized speech manifest personality? Experimental tests of recognition, similarity-attraction, and consistency-attraction. *Journal of Experimental Psychology: Applied*, *7*, 171–181.

Nass, C., & Moon, Y. (2000). Machines and mindlessness: Social responses to computers. *Journal of Social Issues*, *56*, 81–103.

Nath, P., & Mahajan, V. (2008). Chief Marketing Officers: A Study of Their Presence in Firms' Top Management Teams. *Journal of Marketing*, *72*, 65–81.

Nedkovski, V., Guerci, M., De Battisti, F., & Siletti, E. (2017). Organizational ethical climates and employee's trust in colleagues, the supervisor, and the organization. *Journal of Business Research*, *71*, 19–26.

Newell, A., & Simon, H. A. (1972). *Human problem solving* (pp. xiv, 920). Oxford, England: Prentice-Hall.

Nissenbaum, H. (2010). *Privacy in context: Technology, policy, and the integrity of social life.* Palo Alto, CA: Stanford University Press.

Nitzan, I., & Libai, B. (2011). Social Effects on Customer Retention. *Journal of Marketing*, *75*, 24–38.

Novak, T. P. (2020). A Generalized Framework for Moral Dilemmas Involving Autonomous Vehicles: A Commentary on Gill. *Journal of Consumer Research*, *47*, 292–300.

Oliveira, T., Faria, M., Thomas, M. A., & Popovič, A. (2014). Extending the understanding of mobile banking adoption: When UTAUT meets TTF and ITM. *International Journal of Information Management*, *34*, 689–703.

Ordenes, F. V., & Zhang, S. (2019). From words to pixels: Text and image mining methods for service research. *Journal of Service Management*, *30*, 593–620.

Paliwal, M., & Kumar, U. (2009). Kumar, U.A.: Neural networks and statistical techniques: A review of applications. Expert Systems with Applications 36(1), 2-17. *Expert Systems with Applications*, *36*, 2–17.

Pantano, E., & Pizzi, G. (2020). Forecasting artificial intelligence on online customer assistance: Evidence from chatbot patents analysis. *Journal of Retailing and Consumer Services*, *55*.

Papa, A., Mital, M., Pisano, P., & Del Giudice, M. (2020). E-health and wellbeing monitoring using smart healthcare devices: An empirical investigation. *Technological Forecasting and Social Change*, *153*, 119226.

Parasuraman, A. (2000). Technology Readiness Index (Tri): A Multiple-Item Scale to Measure Readiness to Embrace New Technologies. *Journal of Service Research, 2(4), 307-320.*

Parasuraman, A., Berry, L., & Zeithaml, V. (2002). Refinement and reassessment of the SERVQUAL scale. *Journal of retailing*, 67(4), 114.

Parasuraman, R., & Riley, V. (1997). Humans and Automation: Use, Misuse, Disuse, Abuse. *Human Factors*, *39*, 230–253.

Paschen, J., Kietzmann, J., & Kietzmann, T. C. (2019). Artificial intelligence (AI) and its implications for market knowledge in B2B marketing. *Journal of Business and Industrial Marketing*, *34*, 1410–1419.

Paschen, Jeannette, Wilson, M., & Robson, K. (2020). #BuyNothingDay: Investigating consumer restraint using hybrid content analysis of Twitter data. *European Journal of Marketing*, *54*, 327–350.

Paul, J., & Criado, A. R. (2020). The art of writing literature review: What do we know and what do we need to know? *International Business Review*, *29*, 101717.

Paul, J., & Rosado-Serrano, A. (2019). Gradual Internationalization vs Born-Global/International new venture models: A review and research agenda. *International Marketing Review*, *36*.

Paxion, J., Berthelon, C., & Galy, E. (2013). Does driving experience delay overload threshold as a function of situation complexity? In L. Dorn & M. Sullman (Eds.). Driver Behaviour and Training VI. *6th International on Conference Driver Behaviour and Training*, pp.13-23. Finland: International Association of Applied Psychology - IAAP.

Pemer, F. (2020). Enacting Professional Service Work in Times of Digitalization and Potential Disruption. *Journal of Service Research*, *24*(2), 249-268.

Perez-Vega, R., Kaartemo, V., Lages, C. R., Borghei Razavi, N., & Männistö, J. (2021). Reshaping the contexts of online customer engagement behavior via artificial intelligence: A conceptual framework. *Journal of Business Research*, *129*, 902–910.

Peters, D., Calvo, R. A., & Ryan, R. M. (2018). Designing for Motivation, Engagement and Wellbeing in Digital Experience. *Frontiers in Psychology*, *9*, 797.

Petty, R. D. (2000). Marketing without Consent: Consumer Choice and Costs, Privacy, and Public Policy. *Journal of Public Policy & Marketing*, *19*, 42–53.

Pillai, R., Sivathanu, B., & Dwivedi, Y. K. (2020). Shopping intention at AI-powered automated retail stores (AIPARS). *Journal of Retailing and Consumer Services*, *57*, 102207.

Pitardi, V., & Marriott, H. R. (2021). Alexa, she's not human but... Unveiling the drivers of consumers' trust in voice-based artificial intelligence. *Psychology & Marketing*, *38*, 626–642.

Pitt, C., Mulvey, M., & Kietzmann, J. (2018). Quantitative insights from online qualitative data: An example from the health care sector. *Psychology & Marketing*, *35*, 1010–1017.

Pitt, C. S., Bal, A. S., & Plangger, K. (2020). New approaches to psychographic consumer segmentation: Exploring fine art collectors using artificial intelligence, automated text analysis and correspondence analysis. *European Journal of Marketing*, *54*, 305–326.

Pizzi, G., Scarpi, D., & Pantano, E. (2020). Artificial intelligence and the new forms of interaction: Who has the control when interacting with a chatbot? *Journal of Business Research*, *129*, 878-890.

Podsakoff, P. M., MacKenzie, S. B., Bachrach, D. G., & Podsakoff, N. P. (2005). The influence of management journals in the 1980s and 1990s. *Strategic Management Journal*, *26*, 473–488.

Poole, S. M., Grier, S. A., Thomas, K. D., Sobande, F., Ekpo, A. E., Torres, L. T., … Henderson, G. R. (2021). Operationalizing Critical Race Theory in the Marketplace. *Journal of Public Policy & Marketing*, *40*, 126–142.

Poulin, M. J., & Haase, C. M. (2015). Growing to Trust: Evidence That Trust Increases and Sustains Well-Being Across the Life Span. *Social Psychological and Personality Science*, *6*, 614–621.

Poushneh, A. (2021). Humanizing voice assistant: The impact of voice assistant personality on consumers' attitudes and behaviors. *Journal of Retailing & Consumer Services*, *58*, 102283.

Prentice, C., Dominique Lopes, S., & Wang, X. (2020). Emotional intelligence or artificial intelligence– an employee perspective. *Journal of Hospitality Marketing and Management*, *29*, 377–403.

Puntoni, S., Reczek, R. W., Giesler, M., & Botti, S. (2021). Consumers and Artificial Intelligence: An Experiential Perspective. *Journal of Marketing*, *85*, 131–151.

Pwc. (2021). Artificial intelligence market. Retrieved August 10, 2021, from https://www.pwc.com/it/it/publications/assets/docs/pwc-ai-evolution-financial-services.pdf

Pymont, B. C., Morgan, R. P., & Bond, J. R. (1988). The Application of Micro-Modelling to Predicting Total Market Mix Potential. *Journal of Marketing Management*, *3*, 278–295.

Rahman, S. A., Alam, M. M. D., & Taghizadeh, S. K. (2020). Do mobile financial services ensure the subjective well-being of micro-entrepreneurs? An investigation applying UTAUT2 model. *Information Technology for Development*, *26*, 421–444.

Rahman, S. A., Taghizadeh, S. K., Ramayah, T., & Alam, M. M. D. (2017). Technology acceptance among micro-entrepreneurs in marginalized social strata: The case of social innovation in Bangladesh. *Technological Forecasting and Social Change*, *118*, 236–245.

Rai, A. (2020). Explainable AI: from black box to glass box. *Journal of the Academy of Marketing Science*, *48*, 137–141.

Raisch, S., & Krakowski, S. (2021). Artificial Intelligence and Management: The Automation–Augmentation Paradox. *Academy of Management Review*, *46*, 192–210.

Ramadan, Z., Farah, M., & El Essrawi, L. (2021). From Amazon.com to Amazon.love: How Alexa is redefining companionship and interdependence for people with special needs. *Psychology & Marketing*, *38*, 596–609.

Rampersad, G. (2020). Robot will take your job: Innovation for an era of artificial intelligence. *Journal of Business Research*, *116*, 68–74.

Ray, A., Bala, P. K., & Dwivedi, Y. K. (2021). Exploring values affecting e-Learning adoption from the user-generated-content: A consumption-value-theory perspective. *Journal of Strategic Marketing*, *29*, 430–452.

Resnick, B. (2001). Testing a model of exercise behavior in older adults. *Research in Nursing & Health*, *24*, 83–92.

Resnick, P., & Varian, H. R. (1997). Recommender systems. *Communications of the ACM*, *40*, 56–58.

Rhim, J., Lee, G., & Lee, J.-H. (2020). Human moral reasoning types in autonomous vehicle moral dilemma: A cross-cultural comparison of Korea and Canada. *Computers in Human Behavior*, *102*, 39–56.

Riva, G., Baños, R. M., Botella, C., Wiederhold, B. K., & Gaggioli, A. (2012). Positive Technology: Using Interactive Technologies to Promote Positive Functioning. *Cyberpsychology, Behavior, and Social Networking*, *15*, 69–77.

Robinson, S., Orsingher, C., Alkire, L., De Keyser, A., Giebelhausen, M., Papamichail, K. N., Temerak, M. S. (2020). Frontline encounters of the AI kind: An evolved service encounter framework. *Journal of Business Research*, *116*, 366–376.

Rödel, C., Stadler, S., Meschtscherjakov, A., & Tscheligi, M. (2014). Towards Autonomous Cars: The Effect of Autonomy Levels on Acceptance and User Experience. *Proceedings of the 6th International Conference on Automotive User Interfaces and Interactive Vehicular Applications*, 1–8. New York, NY, USA: Association for Computing Machinery.

Rodgers, W., Yeung, F., Odindo, C., & Degbey, W. Y. (2021). Artificial intelligence-driven music biometrics influencing customers' retail buying behavior. *Journal of Business Research*, *126*, 401–414.

Rogers, E. (1995). Diffusion of Innovations. New York: Free Press

Rosado-Serrano, A., Paul, J., & Dikova, D. (2018). International franchising: A literature review and research agenda. *Journal of Business Research*, *85*, 238–257.

Roseman, I. J. (1991). Appraisal Determinants of Discrete Emotions. *Cognition and Emotion*, *5*, 161–200.

Roseman, I. J., Spindel, M. S., & Jose, P. E. (1990). Appraisals of Emotion-Eliciting Events: Testing a Theory of Discrete Emotions. *Journal of Personality and Social Psychology*, *59*, 899–915.

Rosseel, Y. (2012). lavaan: An R Package for Structural Equation Modeling. *Journal of Statistical Software*, *48*, 1–36.

Russell, S. J., & Norvig, P. (1995). *Artificial intelligence: A modern approach*. Englewood Cliffs, N.J: Prentice Hall.

Rust, Roland T., & Huang, M.-H. (2012). Optimizing Service Productivity. *Journal of Marketing*, *76*, 47–66.

Rust, R.T. (2020). The future of marketing. *International Journal of Research in Marketing*, *37*, 15–26.

Ryan, R., & Deci, E. (2001). On Happiness and Human Potentials: A Review of Research on Hedonic and Eudaimonic Well-Being. *Annual Review of Psychology*, *52*, 141–166.

Ryan, R. M., & Deci, E. L. (2000). Intrinsic and Extrinsic Motivations: Classic Definitions and New Directions. *Contemporary Educational Psychology*, *25*, 54–67.

Saborowski, M., & Kollak, I. (2015). "How do you care for technology?" – Care professionals' experiences with assistive technology in care of the elderly. *Technological Forecasting and Social Change*, *93*, 133–140.

SAE International. (2016). J3016A: Taxonomy and Definitions for Terms Related to Driving Automation Systems for On-Road Motor Vehicles. Retrieved August 13, 2021, from https://www.sae.org/standards/content/j3016_201609/

Salminen, K., Farooq, A., Rantala, J., Surakka, V., & Raisamo, R. (2019). Unimodal and Multimodal Signals to Support Control Transitions in Semiautonomous Vehicles. *Proceedings of the 11th International Conference on Automotive User Interfaces and Interactive Vehicular Applications*, 308–318. New York, NY, USA: Association for Computing Machinery.

Sampson, Scott E. (2021). A Strategic Framework for Task Automation in Professional Services. *Journal of Service Research*, *24*, 122–140.

Sampson, S.E., & Chase, R. B. (2020). Customer contact in a digital world. *Journal of Service Management*, *31*, 1061–1069.

Saura, J. R., Palacios-Marqués, D., & Iturricha-Fernández, A. (2021). Ethical design in social media: Assessing the main performance measurements of user online behavior modification. *Journal of Business Research*, *129*, 271–281.

Schepers, J. J. L., & van der Borgh, M. (2020). A Meta-Analysis of Frontline Employees' Role Behavior and the Moderating Effects of National Culture. *Journal of Service Research*, *23*, 255–280.

Schmitt, B. (2020). Speciesism: An obstacle to AI and robot adoption. *Marketing Letters*, *31*, 3–6.

Schuman, H., & Presser, S. (1996). *Questions and Answers in Attitude Surveys: Experiments on Question Form, Wording, and Context*. SAGE.

Schuster, L., Drennan, J., & N. Lings, I. (2013). Consumer acceptance of m-wellbeing services: A social marketing perspective. *European Journal of Marketing*, *47*, 1439–1457.

Schweitzer, F., Belk, R., Jordan, W., & Ortner, M. (2019). Servant, friend or master? The relationships users build with voice-controlled smart devices. *Journal of Marketing Management*, *35*, 693–715.

Shariff, A., Bonnefon, J., & Rahwan, I. (2021). How safe is safe enough? Psychological mechanisms underlying extreme safety demands for self-driving cars. *Transportation Research Part C*, *126*, 1–13.

Shariff, A., Bonnefon, J.-F., & Rahwan, I. (2017). Psychological roadblocks to the adoption of self-driving vehicles. *Nature Human Behaviour*, *1*, 694–696.

Shawar, B. A., & Atwell, E. S. (2005). Using corpora in machine-learning chatbot systems. *International Journal of Corpus Linguistics*, *10*, 489–516.

Shladover, S. E. (2018). Connected and automated vehicle systems: Introduction and overview. *Journal of Intelligent Transportation Systems*, *22*, 190–200.

Shrestha, Y. R., Krishna, V., & von Krogh, G. (2021). Augmenting organizational decision-making with deep learning algorithms: Principles, promises, and challenges. *Journal of Business Research*, *123*, 588–603.

Sidaoui, K., Jaakkola, M., & Burton, J. (2020). AI feel you: Customer experience assessment via chatbot interviews. *Journal of Service Management*, *31*, 745–766.

Silva, E. S., & Bonetti, F. (2021). Digital humans in fashion: Will consumers interact? *Journal of Retailing and Consumer Services*, *60*, 102430.

Singh, J., Nambisan, S., Bridge, R. G., & Brock, J. K.-U. (2021). One-Voice Strategy for Customer Engagement. *Journal of Service Research*, *24*, 42–65.

Singleton, P. A., De Vos, J., Heinen, E., & Pudāne, B. (2020). Chapter Seven—Potential health and well-being implications of autonomous vehicles. In D. Milakis, N. Thomopoulos, & B. van Wee (Eds.), *Advances in Transport Policy and Planning* (pp. 163–190). Academic Press.

Sirgy, M. J., & Lee, D.-J. (2008). Well-being Marketing: An Ethical Business Philosophy for Consumer Goods Firms. *Journal of Business Ethics*, *77*, 377–403.

Sirgy, M. J., Yu, G. B., Lee, D.-J., Wei, S., & Huang, M.-W. (2012). Does Marketing Activity Contribute to a Society's Well-Being? The Role of Economic Efficiency. *Journal of Business Ethics*, *107*, 91–102.

Sisodia, R. S. (1991). Expert Systems for Services Marketing-prospects and Payoffs. *Journal of Services Marketing*, *5*, 37–54.

Sjödin, D., Parida, V., Kohtamäki, M., & Wincent, J. (2020). An agile co-creation process for digital servitization: A micro-service innovation approach. *Journal of Business Research*, *112*, 478–491.

Smith, H. J., Milberg, S. J., & Burke, S. J. (1996). Information Privacy: Measuring Individuals' Concerns About Organizational Practices. *MIS Quarterly*, pp. 167–196.

Smith, K. T. (2020). Marketing via smart speakers: What should Alexa say? *Journal of Strategic Marketing*, *28*, 350–365.

Smith, R. E. (1993). Integrating Information from Advertising and Trial: Processes and Effects on Consumer Response to Product Information. *Journal of Marketing Research*, p. 30(2), 204–219.

Söderlund, M. (2020). Employee encouragement of self-disclosure in the service encounter and its impact on customer satisfaction. *Journal of Retailing & Consumer Services*, *53*, 102001

Sohrabpour, V., Oghazi, P., Toorajipour, R., & Nazarpour, A. (2021). Export sales forecasting using artificial intelligence. *Technological Forecasting and Social Change*, *163*, 120480

Sowa, K., Przegalinska, A., & Ciechanowski, L. (2021). Cobots in knowledge work: Human – AI collaboration in managerial professions. *Journal of Business Research*, *125*, 135–142.

Spiro, R. J., Bruce, B. C., & Brewer, W. F. (2017). *Theoretical Issues in Reading Comprehension: Perspectives from Cognitive Psychology, Linguistics, Artificial Intelligence and Education*. Routledge.

Stahl, B. (2012). Morality, Ethics, and Reflection: A Categorization of Normative IS Research. *Journal of the Association for Information Systems*, *13* (8),1.

Stahl, B. C., Andreou, A., Brey, P., Hatzakis, T., Kirichenko, A., Macnish, K., Wright, D. (2021). Artificial intelligence for human flourishing–Beyond principles for machine learning. *Journal of Business Research*, *124*, 374–388.

Statista. (2021a). • Global artificial intelligence market revenues 2024. Retrieved August 10, 2021, from https://www.statista.com/statistics/694638/worldwide-cognitive-and-artificial-intelligence-revenues/

Statista. (2021b). Global autonomous car market. Retrieved August 10, 2021, from https://www.statista.com/statistics/428692/projected-size-of-global-autonomous-vehicle-market-by-vehicle-type/

Statista. (2021c). Trust in artificial intelligence by country 2018. Retrieved August 10, 2021, from Statista website: https://www.statista.com/statistics/948531/trust-artificial-intelligence-country/

Steckel, J., Winer, R., Bucklin, R., Dellaert, B., Drèze, X., Häubl, G., … Rangaswamy, A. (2005). Choice in Interactive Environments. *Marketing Letters*, *16*, 309–320.

Steenkamp, J.-B., Gielens, K. (2003). Consumer and Market Drivers of the Trial Probability of New Consumer Packaged Goods. *Journal of Consumer Research*, 30(3). 368–384.

Steinberg, M., & Plank, R. E. (1987). Expert systems: The integrative sales management tool of the future. *Journal of the Academy of Marketing Science*, *15*, 55–62.

Steinhoff, L., Arli, D., Weaven, S., & Kozlenkova, I. V. (2019). Online relationship marketing. *Journal of the Academy of Marketing Science*, *47*, 369–393.

Stone, D. (1990). *Stone, E. F., & Stone, D. L. (1990). Privacy in organizations: Theoretical issues, research findings, and protection strategies. In G. Ferris & K. Rowland (Eds.), Research in personnel and human resources management, Vol. 8, (pp. 549-411). Greenwich, CT: JAI Press.*

Su, L., Wan, L. C., & Wyer, R. S. (2018). The contrasting influences of incidental anger and fear on responses to a service failure. *Psychology & Marketing*, *35*, 666–675.

Sundar, S. S. (2008). The MAIN model: A heuristic approach to understanding technology effects on credibility. *Digital Media, Youth, and Credibility*, 73–100.

Tassiello, V., Tillotson, J. S., & Rome, A. S. (2021). “Alexa, order me a pizza!”: The mediating role of psychological power in the consumer–voice assistant interaction. *Psychology and Marketing*.

Thiffault, P., & Bergeron, J. (2003). Monotony of road environment and driver fatigue: A simulator study. *Accident; Analysis and Prevention*, *35*, 381–391.

Thomaz, F., Salge, C., Karahanna, E., & Hulland, J. (2020). Learning from the Dark Web: Leveraging conversational agents in the era of hyper-privacy to enhance marketing. *Journal of the Academy of Marketing Science*, *48*, 43–63.

Thomopoulos, N., & Givoni, M. (2015). The autonomous car—A blessing or a curse for the future of low carbon mobility? An exploration of likely vs. Desirable outcomes. *European Journal of Futures Research*, *3*, 14.

Tigre Moura, F., & Maw, C. (2021). Artificial intelligence became Beethoven: How do listeners and music professionals perceive artificially composed music? *Journal of Consumer Marketing*, *38*, 137–146.

Tong, S., Luo, X., & Xu, B. (2020). Personalized mobile marketing strategies. *Journal of the Academy of Marketing Science*, *48*, 64–78.

Topol, E. J. (2019). High-performance medicine: The convergence of human and artificial intelligence. *Nature Medicine*, *25*, 44–56.

Trope, Y., & Liberman, N. (2010). Construal-Level Theory of Psychological Distance. *Psychological Review*, *117*, 440–463.

Turing, A. M. & Haugeland, J (1950). Computing Machinery and Intelligence. Cambridge, MA: MIT Press.

Vallaster, C., Kraus, S., Lindahl, J. M. M., & Nielsen, A. (2019). Ethics and entrepreneurship: A bibliometric study and literature review. *Journal of Business Research*, *99*, 226–237.

van Doorn, J., Mende, M., Noble, S. M., Hulland, J., Ostrom, A. L., Grewal, D., & Petersen, J. A. (2017). Domo Arigato Mr. Roboto: Emergence of Automated Social Presence in

Organizational Frontlines and Customers' Service Experiences. *Journal of Service Research*, *20*, 43–58.

van Eck, N. J., & Waltman, L. (2010). Software survey: VOSviewer, a computer program for bibliometric mapping. *Scientometrics*, *84*, 523–538.

Van Pinxteren, M. M. E., Pluymaekers, M., & Lemmink, J. G. A. M. (2020). Human-like communication in conversational agents: A literature review and research agenda. *Journal of Service Management*, *31*, 203–225.

van Raan, A. F. J. (2005). Measuring Science. In H. F. Moed, W. Glänzel, & U. Schmoch (Eds.), *Handbook of Quantitative Science and Technology Research: The Use of Publication and Patent Statistics in Studies of S&T Systems* (pp. 19–50). Dordrecht: Springer Netherlands.

van Winsum, W., de Waard, D., & Brookhuis, K. A. (1999). Lane change manoeuvres and safety margins. *Transportation Research Part F: Traffic Psychology and Behaviour*, *2*, 139–149.

Varela-Neira, C., Vázquez-Casielles, R., & Iglesias, V. (2014). Intentionality attributions and humiliation: The impact on customer behavior. *European Journal of Marketing*, *48*, 901–923.

Vargo, S., & Lusch, R. (2016). Service-dominant logic 2025. *International Journal of Research in Marketing*, *34 (1),* 46-67.

Vázquez-Casielles, R., Del Río-Lanza, A. B., & Díaz-Martín, A. M. (2007). Quality of past performance: Impact on consumers' responses to service failure. *Marketing Letters*, *18*(4), 249-264.

Venkatesh, V. (2000). Determinants of Perceived Ease of Use: Integrating Control, Intrinsic Motivation, and Emotion into the Technology Acceptance Model. *Information Systems Research*, *11*, 342–365.

Venkatesh, V., & Davis, F. D. (1996). A model of the antecedents of perceived ease of use: Development and test. *Decision Sciences*, *27*, 451–481.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User Acceptance of Information Technology: Toward a Unified View. *MIS Quarterly*, *27*, 425–478.

Venkatesh, V., Thong, J. Y. L., Chan, F. K. Y., Hu, P. J.-H., & Brown, S. A. (2011). Extending the two-stage information systems continuance model: Incorporating UTAUT predictors and the role of context. *Information Systems Journal*, *21*, 527–555.

Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer Acceptance and Use of Information Technology: Extending the Unified Theory of Acceptance and Use of Technology. *MIS Quarterly*, *36*, 157–178.

Venkatesh, V., Thong, J. Y. L., & Xu, X. (2016). Unified Theory of Acceptance and Use of Technology: A Synthesis and the Road Ahead. *Journal of the Association for Information Systems*, *17*, 328–376.

Verbeek, P.-P. (2015). Beyond interaction: A short introduction to mediation theory. *Interactions*, *22*, 26–31.

Verma, S., Sharma, R., Deb, S., & Maitra, D. (2021). Artificial intelligence in marketing: Systematic review and future research direction. *International Journal of Information Management Data Insights*, *1*, 100002.

Verma, S., & Yadav, N. (2021). Past, Present, and Future of Electronic Word of Mouth (EWOM). *Journal of Interactive Marketing (Elsevier)*, *53*, 111–128.

Villarroel Ordenes, F., & Zhang, S. (2019). From words to pixels: Text and image mining methods for service research. *Journal of Service Management*, *30*, 593–620.

Ville, B. de. (1997). Intelligent tools for marketing research. *Marketing Research*, *9*, 40–43.

Vlačić, B. (2021). The evolving role of artificial intelligence in marketing: A review and research agenda. *Journal of Business Research*, 128, 187-203.

Walker, F., Boelhouwer, A., Alkim, T., Verwey, W. B., & Martens, M. H. (2018). Changes in Trust after Driving Level 2 Automated Cars. *Journal of Advanced Transportation*, *2018*, 1–9.

Walker, K. L. (2016). Surrendering Information through the Looking Glass: Transparency, Trust, and Protection. *Journal of Public Policy & Marketing*, *35*, 144–158.

Wang, C., Boyd-graber, J. C. J., Gerrish, S., Wang, C., & Blei, D. M. (2015). Reading Tea Leaves: How Humans Interpret Topic Models. In *Advances in neural information processing systems,* 288-296.

Wang, H.-I., & Yang, H.-L. (2005). The Role of Personality Traits in UTAUT Model under Online Stocking. *Contemporary Management Research*, *1*, 69–82.

Wang, R. J., & Humphreys, A. (2018). Automated Text Analysis for Consumer. *Journal of Consumer Research*, *44*, 1274-1306.

Wang, S., & Zhao, J. (2019). Risk preference and adoption of autonomous vehicles. *Transportation Research Part A: Policy and Practice*, *126*, 215–229.

Waytz, A., Gray, K., Epley, N., & Wegner, D. M. (2010). Causes and consequences of mind perception. *Trends in Cognitive Sciences*, *14*, 383–388.

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.

Weihrauch, A., & Huang, S.-C. (2021). Portraying Humans as Machines to Promote Health: Unintended Risks, Mechanisms, and Solutions. *Journal of Marketing*, *85*(3), 184-203.

Weiner, B. (2000). Attributional Thoughts about Consumer Behavior. *Journal of Consumer Research*, *27*, 382–387.

Whang, C., & Im, H. (2021). “I Like Your Suggestion!” the role of humanlikeness and parasocial relationship on the website versus voice shopper’s perception of recommendations. *Psychology & Marketing*, *38*, 581–595.

Wiese, E., Metta, G., & Wykowska, A. (2017). Robots as intentional agents: Using neuroscientific methods to make robots appear more social. *Frontiers in Psychology*, *8*, 1–19.

Wilson, R. D., & Bettis-Outland, H. (2019). Can artificial neural network models be used to improve the analysis of B2B marketing research data? *Journal of Business and Industrial Marketing*, *35*, 495–507.

Wilson-Nash, C., Goode, A., & Currie, A. (2020). Introducing the socialbot: A novel touchpoint along the young adult customer journey. *European Journal of Marketing*, *54*, 2621–2643.

Winters, L. C. (1991). Artificial Intelligence and Expert Systems in Marketing. *Marketing Research*, *3*, 72–74.

Wirtz, J., Patterson, P. G., Kunz, W. H., Gruber, T., Lu, V. N., Paluch, S., & Martins, A. (2018). Brave new world: Service robots in the frontline. *Journal of Service Management*, *29*, 907–931.

Wirtz, Jochen, & Lwin, M. O. (2009). Regulatory Focus Theory, Trust, and Privacy Concern. *Journal of Service Research*, *12*, 190–207.

Wirtz, Jochen, & Zeithaml, V. (2018). Cost-effective service excellence. *Journal of the Academy of Marketing Science*, *46*, 59–80.

Xueming Luo, Shaojun Qin, M., Zheng Fang, & Zhe Qu. (2021). Artificial Intelligence Coaches for Sales Agents: Caveats and Solutions. *Journal of Marketing*, *85*, 14–32.

Yadav, M. S., & Pavlou, P. A. (2020). Technology-enabled interactions in digital environments: a conceptual foundation for current and future research. *Journal of the Academy of Marketing Science*, *48*, 132–136.

Yang, S., & Allenby, G. M. (2003). Modeling Interdependent Consumer Preferences. *Journal of Marketing Research*, *40*, 282–294.

Yi, S., & Baumgartner, H. (2004). Coping with negative emotions in purchase-related situations. *Journal of Consumer Psychology*, *14*, 303–317.

Yousafzai, S. Y., Pallister, John. G., & Foxall, G. R. (2005). Strategies for building and communicating trust in electronic banking: A field experiment. *Psychology and Marketing*, *22*, 181–201.

Yun, J. H., Lee, E., & Kim, D. H. (2021). Behavioral and neural evidence on consumer responses to human doctors and medical artificial intelligence. *Psychology & Marketing*, *38*, 610–625.

Zaki, M., & McColl-Kennedy, J. R. (2020). Text mining analysis roadmap (TMAR) for service research. *Journal of Services Marketing*, *34*, 30–47.

Zhang, L., Pentina, I., & Fan, Y. (2021). Who do you choose? Comparing perceptions of human vs robo-advisor in the context of financial services. *Journal of Services Marketing*.

Zhang, Y., Zhang, M., Li, J., Liu, G., Yang, M. M., & Liu, S. (2020). A bibliometric review of a decade of research: Big data in business research – Setting a research agenda. *Journal of Business Research*, *131*, 374-390.

Zhong, J. Y., & Mitchell, V.-W. (2012). Does Consumer Well-Being Affect Hedonic Consumption? *Psychology & Marketing*, *29*, 583–594.

Zhu, J. J., Chang, Y.-C., Ku, C.-H., Li, S. Y., & Chen, C.-J. (2021). Online critical review classification in response strategy and service provider rating: Algorithms from heuristic processing, sentiment analysis to deep learning. *Journal of Business Research*, *129*, 860–877.

Appendices

Appendix 1. Description of the Service Failure

Please, imagine the following situation: You are travelling for a business trip. You have just arrived at the airport after a long trip of 10 hours. You exit the airplane and go to the baggage claim area to collect your luggage. You're standing at the baggage carousel for what seems like forever and there is no sign of your suitcase anywhere. You are informed that your suitcase and all your personal belongings are missing. Thus, you submit a form on the live chat to declare your missing luggage and you receive a reference number. After a few days you still do not have any information concerning your missing luggage. So you contact the live chat agent to ask for more information and you are put through the human service agent/ airline chatbot.

Appendix 2. Script of the Videos

Service agent: Hi there. My name is Jack. I am the customer service representative of the Airline/ I am the airline bot. How can I help you?

Customer: Hi, my luggage is lost.

Service agent: I am sorry to hear that! Don't worry; I am going to help you with that. Have you already declared your missing luggage?

Customer: Yes

Service agent: Could you write your claim number, please?

Customer: CDGAF12345

Service agent: Ok thank you. I am going to check. I am sorry but I cannot find any claim associated with that number. Please, could you write the reference number again? Make sure that no mistake occurs.

Customer: CDGAF12345. I am sure that this is the correct reference number.

Service agent: I am sorry but unfortunately I can't find any claim associated with this number. I cannot find any information about your missing luggage.

Customer: How is that possible?

Service agent: I guess that a mistake has occurred. Try to declare again your missing baggage by providing the baggage receipt number. I suggest adding as many details as possible in your luggage description such as type of bag, colours and any other distinctive features. Customer: But I have already done it two days ago!

ABSTRACT

Artificial Intelligence (AI) is often considered as one of the most promising and disruptive innovation of our times. Despite its rapid development, there is still a high level of uncertainty about how consumers are going to adopt AI. In this context, this four-article dissertation aims to comprehend how consumers use and interact with intelligent technologies, in particular focusing on two current applications: chatbots and autonomous vehicles (AVs). First, we conduct an in-depth analysis of the existing marketing literature adopting Scientometric and Theory-Context-Characteristics-Methodology approaches. Thus, we define our research questions related to 1) consumers 'cognitive and emotional reactions when interacting with AI-based technologies that are able to simulate human-like conversations; 2) factors affecting consumers 'intention to use AI-based technologies able to make decision in critical situations, and their evolution across levels of automation; 3) consumers ethical concerns towards AI products and their effect on trust and usage intentions. By applying three between-subject experimental designs, we answer our first research question comparing human–human versus human–chatbot interactions and highly anthropomorphic versus lowly anthropomorphic chatbots. We leverage insights mainly from Cognitive Appraisal Theory of Emotions (Roseman et al. 1990), Attribution Theory (Weiner 2000) and Theory of Anthropomorphism (Aggarwal and McGill 2007; Epley et al. 2018), showing that consumers' responses differ when interacting with a human and a chatbot, according to the different attributions of responsibility and the different levels of anthropomorphism of the service agent. Next, we investigate the way consumers' experience with different levels of automation affect perceptions of AI-based technologies. We use AVs as unit of analysis, integrating the UTAUT framework with Trust Theory (Mcknight et al. 2011), Privacy Calculus Theory (Dinev and Hart 2006) and Theory of Well-being (Diener 1999; Diener and Chan 2011). After implementing a within subject-design with field and simulator studies, results suggest that differentiating between the different automation levels play a key role to better understand the potential drivers of adoption as well as the cognitive reactions when using intelligent applications. Finally, we investigate consumers' ethical concerns surrounding chatbots and AVs. We employ a mixed methods approach, using topic modeling and structural equation modeling. We show that for chatbots, the interactional and emotional component of the technology is predominant, as consumers highlight, between others, the emotional design and the lack of adaptability as main ethical issues. However, for autonomous cars, the ethical concerns rather involve cognitive perceptions related to the transparency of the algorithms, the ethical design, the safety of the technology and the accessibility. Our research offers contributions to the emerging literature on consumer behaviors related to intelligent products by highlighting the need to take into account the complexity of AI technologies across their different levels of automation and according to their intrinsic characteristics. We also offer methodological contributions thanks to the implementation of innovative experimental research designs, using advanced tools and combining qualitative and quantitative approaches. To conclude, we present implications for both managers and policymakers who want to implement AI-based disruptive technologies, such as chatbots and AVs.

Keywords: artificial intelligence; autonomous cars; chatbots; cognitive and emotional responses; ethics; experimental design; mixed-methods; field study; simulator study

RÉSUMÉ

L'intelligence artificielle (IA) est souvent considérée comme l'une des innovations les plus prometteuses et perturbatrices de notre époque. Malgré son développement rapide, il existe encore un haut niveau d'incertitude quant à la manière dont les consommateurs vont adopter l'IA. Dans ce contexte, cette thèse de quatre articles vise à comprendre comment les consommateurs utilisent et interagissent avec les technologies intelligentes, en se concentrant en particulier sur deux applications: les chatbots et les véhicules autonomes (VA). Dans un premier temps, nous effectuons une analyse approfondie de la littérature marketing existante en adoptant les approches scientométriques et la methode *Theory-Context-Characteristics-Methodology*. Ainsi, nous définissons nos questions de recherche concernant 1) les réactions cognitives et émotionnelles des consommateurs lorsqu'ils interagissent avec des technologies basées sur l'IA capables de simuler des conversations de type humain ; 2) les facteurs affectant l'intention des consommateurs d'utiliser des technologies basées sur l'IA, et leur évolution à travers les niveaux d'automatisation ; 3) les préoccupations éthiques des consommateurs envers les produits IA et leur effet sur la confiance et les intentions d'utilisation. En mettant en œuvre trois plans expérimentaux inter-sujets, nous répondons à notre première question de recherche en comparant les interactions humain-humain et humain-chatbot et les interactions avec des chatbots hautement anthropomorphes et faiblement anthropomorphes. Nous nous appuyons principalement sur la Théorie de l'Evaluation Cognitive des Emotions (Roseman et al. 1990), la Théorie de l'Attribution (Weiner 2000) et la Théorie de l'Anthropomorphisme (Aggarwal and McGill 2007 ; Epley et al. 2018), en montrant que les réponses des consommateurs diffèrent lorsqu'ils interagissent avec un humain et un chatbot, en fonction des différentes attributions de responsabilité et des différents niveaux d'anthropomorphisme. Ensuite, nous étudions la manière dont l'expérience des consommateurs avec différents niveaux d'automatisation affecte les perceptions des

technologies basées sur l'IA. Nous utilisons les VA comme unité d'analyse, en intégrant le cadre UTAUT avec la Théorie de la Confiance (Mcknight et al. 2011), la Théorie du Calcul de la Vie Privée (Dinev et Hart 2006) et la Théorie du Bien-être (Diener 1999). Après la mise en œuvre d'un design intra-sujet avec des études sur le terrain et sur simulateur, les résultats suggèrent que la différenciation entre les différents niveaux d'automatisation joue un rôle clé pour mieux comprendre les facteurs d'adoption ainsi que les réactions cognitives lors de l'utilisation d'applications intelligentes. Enfin, nous étudions les préoccupations éthiques des consommateurs concernant les chatbots et les VA. Nous utilisons une approche mixte, en utilisant la modélisation thématique et la modélisation par équation structurelle. Nous montrons que pour les chatbots, la composante interactionnelle et émotionnelle de la technologie est prédominante, les consommateurs soulignant, entre autres, le design émotionnel et le manque d'adaptabilité comme principaux soucis éthiques. En revanche, pour les VA, les préoccupations éthiques concernent plutôt des perceptions cognitives liées à la transparence des algorithmes, à la sécurité de la technologie et à l'accessibilité. Notre recherche offre des contributions à la littérature émergente sur les comportements des consommateurs liés aux produits intelligents en soulignant la nécessité de prendre en compte la complexité des technologies d'IA à travers leurs différents niveaux d'automatisation et en fonction de leurs caractéristiques. Nous offrons également des contributions méthodologiques grâce à la mise en œuvre de plans de recherche expérimentaux innovants, utilisant des outils avancés et combinant des approches qualitatives et quantitatives. Pour conclure, nous présentons des implications à la fois pour les managers et les décideurs politiques qui souhaitent mettre en œuvre des technologies basées sur l'IA, telles que les chatbots et les VA.

Mots clés : intelligence artificielle ; voitures autonomes ; chatbots ; réponses cognitives et émotionnelles ; éthique ; conception expérimentale ; méthodes mixtes ; étude de terrain ; étude sur simulateur