UNIVERSITY OF SALERNO

Department of Economics and Statistics

PhD Course

ECONOMIA E POLITICHE DEI MERCATI E DELLE IMPRESE

XXXIII Ciclo

Curriculum

MARKETING MANAGEMENT

Doctoral Thesis

Emotional Artificial Intelligence: Detecting and Managing Customer Emotions in Automated Customer Service

Supervisor
Prof. Marialuisa Saviano

Coordinator
Prof. Alessandra Amendola

Co-Supervisor
Prof. Mathieu Lajante

Mathieu Lajante

Candidate:
Dr. Marzia Del Prete
8801000037

Academic Year 2020-2021

Dedicated to:
my daughter Rebecca,
my grandmother Carmela,
my friend Marisa.

Human behavior flows from three main sources:
desire, emotion, and knowledge.
Plato.

Acknowledgments

I am deeply indebted to my supervisors for their advice at different stage of writing this doctoral thesis.

Professor Marialuisa Saviano offered constructive criticism and substantial suggestions all along the variegated development of this dissertation. The numerous and lengthily conversations I had with her were a constant source of inspiration and wide perspectives. Her timely advice, meticulous scrutiny, academic guidance and scientific approach have helped me to a very great extent to accomplish this work.

All my esteem and gratitude go to Professor Mathieu Lajante for welcoming me into the Marketing Department of Laval University in Canada and giving me the opportunity to start a research path aimed at studying customer emotions in automated service encounters. His always available assistance was essential and his influence is clearly visible throughout Chapter 4. I thank prof. Lajante also for having always believed in me and in my scientific assessments by funding the empirical research of this work.

My debt to Professor Marialuisa Saviano and Professor Mathieu Lajante goes beyond this dissertation.

Finally, I thank the Coordinator of the PhD Programme, Professor Alessandra Amendola for her availability during these three years of doctorate in which I was able to mature and live multidisciplinary learning experiences aimed at my human and academic growth.

Table of Contents

List of Figures

List of Tables

ABSTRACT

Among the distinctive features of the human race are the ability to feel emotions and to be empathetic with others. These features are strictly related to the concept of emotional intelligence (EI). In this thesis, the skills of EI have been explored in the context of automated customer service, to achieve effective customer engagement through the emotional reading of their needs and moods. Contact center operators are often trained to detect different emotional states and connect empathically with customers, to engage them in new commercial offers or solve their main problems both in the pre-sales and post-sales processes. Frontline employees (FLEs) use their empathetic skills to prevent negative emotions and transform complex issues into positive solutions for the customer.

Emotional awareness and empathy are important assets in customer relationship management (CRM) to establish the customer's loyalty and advocacy towards the firm in a logic of value co-creation.

Customer service automated systems see artificial intelligence (AI) become part of this scenario with a consequent loss of empathic capacity in the interaction between customers and firms due to an incorrect reading and managing of customer emotions.

The aim of this thesis is to evaluate how a customer service AI technology called *chatbot*s affect this interaction and detect customer emotions, expectations, and service quality perceptions effectively. This work develops a new conceptual framework that combines the skills of emotional intelligence (EI) with those of current AI-powered chatbots already operating in many customer service systems. The emotional artificial intelligence (EAI) framework represents a possible way for a chatbot to know when a human agent must intervene to handle a complicated conversation with the customer without a loss of empathic capacity of the firm.

Currently, AI-powered chatbots represent 80% of the front-end of firms, and in order to better interact with customers, they need to play an incremental role in improving the customer experience (CX). A chatbot uses machine learning algorithms to analyze customer conversations as they occur.

We argue that these algorithms may be able to capture an emotional map of the automated and omnichannel customer journey through the components of emotional artificial intelligence (EAI).

The EAI framework, in its principal emotional artificial awareness component, does not provide for the complete replacement of human operators by chatbots, even if the latter are equipped with emotional reading skills. Emotional awareness is necessary for chatbots only to define the switch point in which a complex issue must be diverted to a human operator so that he/she can find the right solution with empathy and establish an emotional connectedness in the manner of an interhuman service encounter.

The switch point is a very complex issue and requires the chatbot to recognize the main customer emotions (positive, neutral or negative) during service encounters. For this reason, in the first chapter of this thesis, we started a literature review on emotions (in particular discrete emotions) during firm-customer encounters and in the second chapter, we contributed to give a literature overview on automated service technologies with a focus on emotional and artificial intelligence in the customer service context.

Another important aspect in support of our EAI framework is the understanding of how the emotional awareness of chatbots may affect the acceptance of these AI-tools by the customer, which is why in the fourth chapter we designed an empirical research framework on the sRAM model (Wirtz et al., 2018), which is preparatory and functional to the validation of our EAI model, described in the third chapter. Below is the complete structure of the chapters.

The first chapter introduces a literature review of emotions and EI during service encounters, with particular emphasis on the appraisal of emotions and the emotion process in relation to different firm-relevant outcomes. The literature review concludes with a reading of the analytical path carried out through the main theories on EI.

The second chapter opens with a literature overview on emotional and artificial intelligence in the customer service context. It explores the theoretical background of EI in the customer relationship management (CRM) field and that of AI for its related automations. The theme of agents and robots in service research is explored in 360 degrees to focus the attention on AI technologies called “chatbots”. The second chapter concludes with observations regarding the value co-creation and co-disruption in human-like interactions in automated customer service.

The third chapter outlines our EAI framework for an automated customer journey. The EAI is described in its main components and new provisioning is drawn to manage complex issues through emotional recognition during automated service encounters.

The fourth and final chapter defines chatbots’ acceptance according to the sRAM model by Wirtz et al. (2018) through a cross-sectional research design and a self-administered questionnaire on 301 millennials, with a specific focus on technology literacy and emotional awareness as its potential moderators.

One of the main purposes of the fourth chapter is to verify the significance of emotional awareness on chatbots’ acceptance. In particular, we argue that the chatbots’ ability to recognize emotions is significant for customer acceptance and preparatory to the validation of our EAI framework. In our empirical analysis, we have also put a specific focus on the recognition of the two discrete emotions of guilt and happiness for the reasons that emerged from the literature review in the first chapter.

The results validate and empirically extend the sRAM model, showing that not only functional but also social and relational elements drive the adoption of chatbots; untangle the crossover effects between them; and reveal the moderating effect of technology literacy and emotional awareness. Furthermore, the study concludes that it is not only the functional elements that determine the acceptance of chatbots but above all the relational ones that can be strengthened, through emotional awareness, for customer-chatbot rapport building. We argue that this *rapport* will allow the chatbot to identify the switch point and allow the human operator to manage complex issues.

The contributions of this thesis are manifold. First, we help to fill a gap in the literature, as research on emotions and automated technologies is still in its infancy and has been largely conceptual. Second, we offer the first attempts to investigate the contribution of the EAI framework to value co-creation by designing the first emotional map based on discrete emotions in automated customer service. The touchpoints that customers encounter through the entire customer experience are mapped from a satisfaction point of view but in literature, there is a gap of metrics including affect and in particular emotions.

Third, we offer a pioneering study that empirically validates the sRAM model by Wirtz et al. (2018), considering chatbots as a specific technology and a cohort (millennials). The sRAM model is one of the few that incorporates both the social and relational characteristics of service robots. We extend the sRAM model by validating direct effects and incorporating the moderating role of technology literacy and emotional awareness, as yet unexplored in the technology acceptance literature, including social robots and AI devices.

The empirical research is needed for a first validation of the EAI framework. The thesis also provides managerial guidance on how to successfully implement chatbots in automated customer service considering the fundamental role of customer emotions for customer engagement and value co-creation.

CHAPTER 1. THE ROLE OF EMOTIONAL INTELLIGENCE (EI) AND EMOTIONS IN SERVICE ENCOUNTERS: A LITERATURE REVIEW

1.1 Emotional Intelligence and Emotions in Firm-Customer Encounters

According to Goleman (1995) and Mayer and Salovey (1997), emotional intelligence (EI) is the capacity to identify, express, understand, manage, and use emotions.

A high level of EI is related to better social and intimate relationships (Lopes et al., 2004; Lopes et al., 2005). The construction of this "intimate" relationship (or rapport) between service employees and customers is functional to a perfect customer engagement and cannot be separated from work on EI.

In a context where services are increasingly automated (with the advent of AI) and customer journeys become omnichannel (Lemon and Verhoef, 2016), an important way for firms to differentiate themselves and gain competitive advantage on the market, is certainly represented by the role of EI for customer service employees (Grönroos, 2007) or conversational agents (chatbots) in recognizing and managing customers' emotional states by co-creating value (Vargo et al., 2008) and not losing it (Čaić et al., 2018).

The omnichannel customer journey and the choices related to its automation represent one of the challenges of the global market that the governance of firms must face (Bell et al., 2014; Brynjolfsson et al., 2013; Piotrowicz and Cuthbertson, 2014; Verhoef et al., 2015).

The progress in information and communication technology has led to an increase in the channels through which customers can contact a firm during a service interaction. In addition to traditional physical and online stores, new mobile channels (mobile devices, branded apps, social media, and connected objects) and touchpoints have transformed the firm-relevant outcomes such as *evaluation*, *purchase* and *sharing behaviors* (Juaneda-Ayensa et al., 2016; Melero et al., 2016; Picot-Coupey et al., 2016; Piotrowicz and Cuthbertson, 2014; Verhoef et al., 2015).

In this complex context, choosing to entrust an initial interaction with a customer to an instrument of AI such as a conversational agent (chatbot) implies that the chatbot, like a human operator, must be able to perceive and recognize the customer's emotional state in order to promptly manage their requests and fully satisfy them.

The managerial problem that emerges in this investigation is linked to the theme of the recognition and management of customer emotions during automated service encounters. Recognizing customer's emotions in order to fully manage their requests during a service interaction has positive effects on customers' intentions to return and to recommend the service to others (Grandey, 2003). Timely emotional awareness of customer's negative emotions by service employees can lead to complex problem solving and establish an emotional connectedness with customers as a basis of a solid intimate and empathic relationship (Pansari and Kumar, 2017).

The recent popularity of EI and its influence on various aspects of business has inspired many EI interventions (Daus and Cage, 2008). A literature review of the existing research is important to understand the methodological shortcomings related to emotions and EI in service encounters, thereby allowing us to know the state-of-the-art about the awareness of customers emotions in every touchpoint of an omnichannel customer journey (Lemon and Verhoef, 2016).

Before talking about EI, however, it is necessary to have an understanding of the theoretical background behind the definition of emotion, its process and its appraisal. Emotional intelligence is, in fact, related to the management of emotion starting with awareness. For this reason, the mechanisms underlying the emotional processes, the definition of emotion itself and the consequent differentiation from terminologies with which it is often confused such as *mood* or *feeling* (Bagozzi et al., 1999 ; Frijda et al., 1989; Lerner and Keltner, 2000; Russel, 2003; Kranzbühler et al., 2020), the theories of appraisal (Ellsworth and Scherer, 2003; Smith and Ellsworth, 1985) and the most used frameworks (Han et al., 2007; Lerner and Keltner, 2000; Roseman, 1991; So et al., 2015) must support and act as a basis to the present investigation. The analysis concludes with a study of the management of emotion through theories of EI.

The first part of this chapter will explore the literature about the role of emotions in service encounters.

In the second part, the focus will be the management of discrete emotions that will emerge from the analysis of the literature through EI theories and the choice of the two most significant emotions (one with a positive value and the other with a negative value) to be managed during a service interaction with a frontline employee (FLE) or conversational agent (chatbot).

This chapter aims to understand the construct of emotions and the main models associated with them in relation to the main firm-relevant outcomes in an omnichannel customer journey, because whatever the interaction tool (human operator or conversational agent) with which a firm wants to equip itself in its front-end strategy, emotional awareness of customer emotions is the basis of this interaction.

1.2 Methodology

The aim of this literature review is to classify and summarize research that is relevant to emotion and EI in service encounters.

The review method is based on the guidelines offered by Booth, Papaioannou and Shutton (2012). In compliance with these indications, and in order to contextualize them to the specific field of interest explored, the analysis of the literature is based on the prior identification of five research question which will also frame the potential interpretative contribution offered.

The five research questions (RQ) that are investigated in the literature review are as follows:

RQ1: Is a focus on emotions able to give added value in service encounters?

RQ2: Do different appraisals of emotions differently affect outcomes during a service encounter?

RQ3: Do specific appraisals of emotions differently affect each of the three outcome variable categories of *evaluation, purchase behavior,* and *sharing behavior*?

RQ4: Do discrete emotions differently affect each of the three outcome variable categories of *evaluation, purchase behavior*, and *sharing behavior*?

RQ5: Is the EI of service employees able to moderate the effects of discrete emotions during service encounters?

To answer the five RQ outlined, we summarized the existing research on the effects of discrete emotions and their appraisal patterns on the outcome of firm-customer encounters. To analyze discrete emotions, we considered the study of Ruth et al. (2002) and their 10 core consumption emotions: love, happiness, gratitude, guilt, pride, fear, sadness, anger, embarrassment, and uneasiness. For the emotion process, we considered the studies of Scherer and Moors (2019).

Following previous research by Goleman (1995), we based our analysis on EI theories to highlight the studies on the management and regulation of discrete emotions.

The research is divided into three stages: a literature search (Stage 1), assessing the evidence base (Stage 2) and analyzing and synthesizing the findings (Stage 3). In stage one we selected studies containing at least one of the terms *emotion*, emotions*, emotional*,* and *intelligence** in combination with terms suggesting a context of firm-customer encounters (*service encounters**, *customer*, consumer*,* and *firm**) in the titles, abstracts or keywords of articles and books searched. To identify a set of studies investigating the above items we searched multiple databases (EBSCO, Web of Science and Google Scholar). We chose EBSCO because their database includes a check with citation databases, such as Scopus, in addition to reference research ones, such as PsycINFO and SciFinder, to determine relevance and quality. We also checked the reference lists of previous studies offering an overview of emotions and affect in marketing (e.g., Bagozzi et al., 1999; Richins, 1997) and of emotion process (Scherer and Moore, 2019). Finally, we checked the EI theories to manage and regulate discrete emotions.

During our literature review, we observed that articles on emotion and EI in service encounters cut across disciplines, including marketing, service, management, psychology, neurobiology, engineering, computer science, medical physics, and biomedical engineering. Hence, conducting a comparative analysis of articles is difficult since different journals and different scientific domains have different research focuses and methodologies.

For this reason, in stage one, we focused on the journals that were most likely oriented towards marketing, service, and management in a combined search with psychology and computer science journals.

The search resulted in articles published in the top marketing, service, management, psychology, and computer science journals that featured at least one of the eight keywords in the title, abstract or keywords. The search extended across the period of 1970 to January 2020 and covered **1701 articles.**
In stage two, the suitability of the articles for review was assessed. When the title and abstract did not reveal the content of the paper, the full paper was read to determine whether the article was appropriate for this study (*first level of coherence*). Subsequently, following the reading of the full papers, we selected the contributions that were deemed to offer useful elements for the interpretation and resolution of the six research questions (*second level of coherence*).

According to the criterion of *afference*, any duplicates or anonymous papers were eliminated.

We used two exclusion criteria. We excluded the studies in which our search words were mentioned in the abstract or keywords, but the authors did not discuss them in the full text (exclusion criterion 1). We excluded meeting abstracts, workshop descriptions, masters and doctoral dissertations, and non-English articles (exclusion criterion 2).

Ultimately, we selected **78 articles** for our final analysis.

Then in stage three, we analyzed the selected 78 articles. The analysis included four steps: documenting, attaining basic understanding, coding, and categorization. First, the details of the articles were documented using Microsoft Excel including the year of publication and the journal name. Second, the selected articles were read to become familiar with the research field and understand how the studies have developed over time. Third, whenever content related to emotion and EI in service encounters was found, it was annotated and coded for its message or content.

The flow chart of the literature review is presented in Figure 1.

Figure 1: Flowchart of Publications Included and Excluded during the Selection Procedure and Consecutive Methodologic Steps of the Literature Review

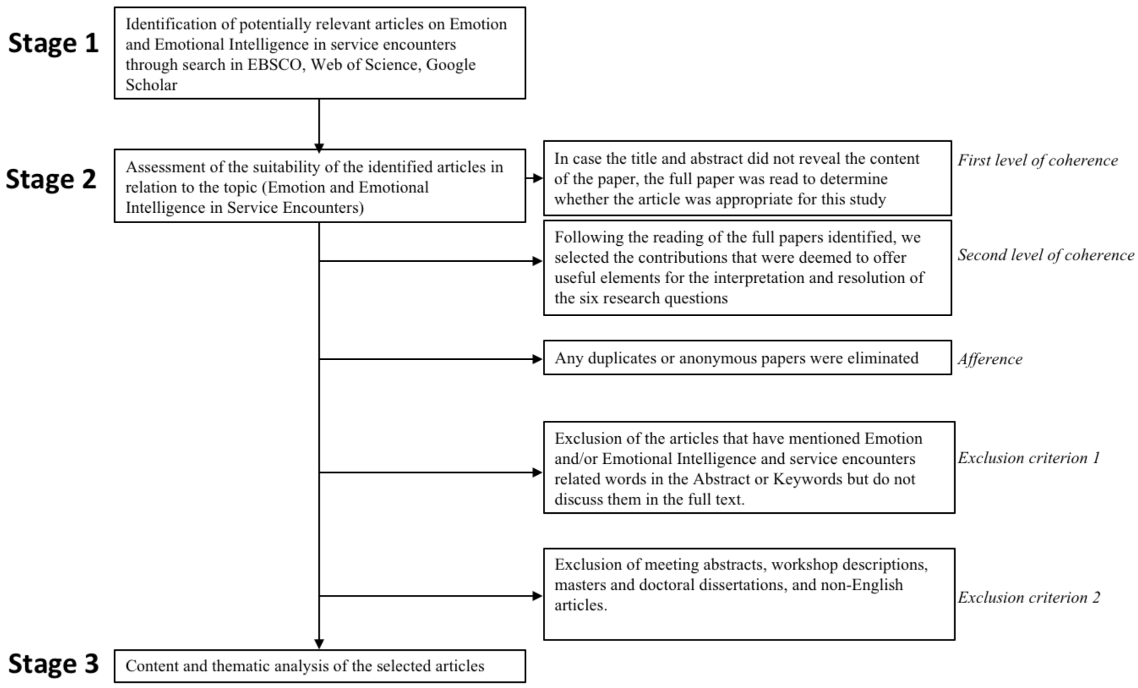


Table 1 shows the thematization of the reviewed articles in relation to the five RQ.

Table 1: Thematization of Reviewed Articles

Research Questions	Theme	References	Number of Articles	Percentage
RQ1	Emotion in marketing	Frijda et al. 1989; Cohen and Areni 1991; Frijda 1993; Richins 1997; Bagozzi et al. 1999; Goleman 1999; Lerner and Keltner 2000; Tiedens and Linton 2001; Pugh 2001; Tsai and Huang 2002; Russel 2003; Finn 2005; Laros and Steenkamp 2005; Zeelenberg et al. 2008; Lench et al. 2011; Grappi et al. 2015; Keltner and Horberg 2015; Puccinelli et al. 2016; Pansari and Kumar 2017; Ou and Verhoef 2017; Kranzbühler et al. 2020.	21	27%
RQ2	Process and appraisal of emotion	Schwartz et al. 1981; Roberts and Weerts 1982; Ekman et al. 1983; Lazarus 1991;Gentsch et al 2014; Roseman 1991; Roseman 1996; Smith and Ellsworth 1985; Lerner and Keltner 2001; Van Dijk and Zeelenberg 2002; Ruth et al. 2002; Lerner et al. 2003; Ellsworth and Scherer 2003; Han et al.2007; Frijda and Scherer 2009; Scherer 2009a; Aue and Scherer 2011; Mulligan and Scherer 2012; So et al. 2015; Scherer and Moors 2019.	20	25%
RQ3, RQ4	Change in relevant outcomes	Kaplan et al. 1974; Johnson and Zinkhan 1991; Bettencourt and Gwinner 1996; Jayanti 1996; Damasio 1996; Menon and Dubé 2000; Mattila and Enz 2002; Coulter and Ligas 2004; Kernbach and Schutte 2005; Hennig-Thurau et al. 2006; Carter and Porges 2011; Moe and Schweidel 2011; Malthouse and Calder 2011; Berger 2014; Wang et al 2015; Watson 2015; Kasnakoglu et al. 2016; Eisenberg 2016; Eisingerich et al. 2015; Magids et al. 2015; Blom et al. 2017; Mosquera et al. 2017; Brodie et al. 2011; Lin and Lin 2011.	23	29%
RQ5	EI Theories	Goleman 1995; Lu et al. 2011; Tam 2004; Homburg et al. 2009; Tsarenko and Tojib 2011; Laroche et al. 2004; Aziz 2008; Sirianni et al. 2013; Robbins 2013; Sheppes et al. 2014; Gross 2015a; Koole 2009; Tamir 2016; Ford and Gross 2018.	14	18%
Total			78	100%

In summary, the literature review involved **68 journal** articles and **10 books**.

Table 2 highlights an overview of the publication selected in relation to the knowledge area and journals.

Table 2: Overview of the Publication Selected and Journals

Knowledge Area	Number of pubblication in journals	Total Percentage
Marketing	**22**	**32%**
Health Marketing Quarterly	1	
Icono 14	1	
Journal of the Academy of Marketing Science	3	
Journal of Business Research	2	
Journal of Consumer Psychology	4	
Journal of Consumer Research	1	
Journal of International Marketing	1	
Journal of Marketing	3	
Journal of Marketing Management	1	
Journal of Retailing	1	
Journal of Retailing and Consumer Services	1	
Journal of the Academy of Marketing	1	
Marketing Science	1	
Marketing Science Institute Working Paper Series	1	
Service	**9**	**13%**
Journal of Service Management	1	
Journal of Service Research	4	
Journal of Services Marketing	4	
Psychology	**29**	**43%**
American Psychologist	1	
Annual Review of Psychology	1	
Biological Psychology	2	
Canadian Psychology	1	
Cognition and Emotion	5	
Emotion review	1	
Journal of Applied Psychology	3	
Journal of Experimental Psychology	1	
Journal of Personality and Social Psychology	4	
Motivation and Emotion	1	
Personality and Social Psychology Review	1	
Philosophical Transactions of the Royal Society of London. Series B: Biological Sciences	1	
Psychological Bulletin	1	
Psychological Inquiry	1	
Psychological Reports	1	
Psychological Review	1	
Psychological Science	1	
Psychosomatic Medicine	1	
Science	1	
Management	**7**	**10%**
Academy of Management Journal	1	
European Management Journal	1	
Harvard Business Review	1	
International Journal of Economics and Management	1	
International Journal of Services Industry Management	1	
Judgment and Decision making	1	
Total Quality Management	1	
Computer Science (miscellanous)	**1**	**1%**
International Journal of Advanced Computer Science & Applications	1	
Total	**68**	**100%**

Table 3 shows an overview of the books and conference papers selected in relation to the knowledge area.

Table 3: Overview of Selected Books

Knowledge Area	N. Books	Percentage
Marketing	1	9%
Psychology	8	73%
Management	1	18%
Total	**10**	**100%**

1.3 Findings

In the following paragraphs, we discuss the findings of our literature review in relation to our five research questions (RQ) outlined above.

1.3.1 The role of emotions in firm-customer encounters (RQ1)

The role of emotions during firm-customer encounters is really important for customer evaluation and behavior (Bagozzi et al., 1999; Richins, 1997).

A key competence of service employees or conversational agents is to be able to recognize these emotions and to operate a mitigation action when negative emotions or a commercial proposition in case of positive emotions occurs during an interaction with the customer, all this can impact the customers' evaluation of the firm (Pugh, 2001).

Emotional intelligence (Goleman, 1999), therefore, appears to be an essential component for service employees or conversational agents, and the only one capable of establishing an emotional connectedness (Pansari and Kumar, 2017) with the customer in order to recognize their emotional state.

A strictly valence-based approach (Puccinelli et al., 2016) to the construct of emotions, much used in customer experience literature (Finn, 2005; Ou and Verhoef, 2017; Tsai and Huang, 2002), is not enough because it sacrifices the specificity of the effect of emotions in many settings (Laros and Steenkamp, 2005; Richins, 1997).

Keltner and Horberg (2015) argue that physiological reactions, judgement, decision making, and coping strategies can be different for customers on many levels, in relation to emotions with the same valence. For this reason, many psychologists suggest studying discrete emotions (Lench et al., 2011; Lerner and Keltner, 2000; Tiedens and Linton, 2001; Zeelenberg et al., 2008).

Customer behavior and judgement are influenced by different discrete emotions and their effects.

For example, gratitude impacts on willingness to pay, while happiness does not, even though both of these emotions have a positive valence (Grappi et al., 2015).

In light of this, with the motivation to increase the EI of conversational agents (chatbots) in its main component of emotional awareness, it is imperative to review the different effect of discrete emotions and examine their impact on judgements and behaviors along the customer journey. It is important to understand how the EI of service employees or conversational agents (chatbots) impacts the awareness of the customer's discrete emotions and how this capability changes the situational characteristics and the main firm-relevant outcomes along the customer journey (evaluation, purchase behavior, sharing behavior).

For this reason, the following topics will be studied in depth through an analysis and subsequent rethinking of the existing literature: 1) the theory and function of emotions; 2) the emotion process and appraisal; 3) the interaction and change in relevant outcome variables in firm-customer encounters (evaluation, purchase behavior, and sharing behaviors) and the moderation of situational characteristics (in particular the personal interaction with FLEs); 4) the management and regulation of emotion according to EI theories.

1.3.2 Definition and function of emotions (RQ1)

Customer experience, evaluations, and actions are based on emotions (Bagozzi et al., 1999).

According to the definition supported by many authors (Bagozzi et al., 1999; Frijda et al., 1989; Lerner and Keltner, 2000; Russel, 2003; Kranzbühler et al., 2020), emotion is a mental state of readiness triggered by a change of *core affect*, often accompanied with a variance of at least one of the two variables of *valence* and *arousal.* Emotion is processed by cognition through an appraisal that defines the *referent* (cause) and the *assessment* (meaning) of this change of core affect.

In its phenomenological tone, emotion is manifested through a physiological process often expressed physically (e.g., gestures, facial expressions, posture) and may result in specific actions to affirm or cope with emotions (Bagozzi et al.,1999). The term *affect* is used as an umbrella among the terms of *emotions*, *moods* and *attitudes* (Bagozzi et al., 1999).

The principal differences between moods and emotions are: a) a mood is longer lasting and lower in intensity than an emotion (Bagozzi et al., 1999); b) a mood is in general non-intentional or diffused whereas an emotion has often an intentional object or referent (Frijda, 1993); c) a mood is not associated with specific actions as are many emotions (Bagozzi et al., 1999; Frijda et al., 1989; Russel, 2003).

As for *attitudes*, the topic is debated in the literature. Many authors claim that they derive from *affect* as well as *emotions* and *moods*; others, such as Cohen and Areni (1991), think attitudes are separate and comparable to *evaluative judgments*, measured by good-bad reactions rather than emotional states.

It is important to recognize that the terms *affect*, *emotions*, *moods* and *attitudes* have frequently been used inconsistently in literature and that terminological confusion is not useful for understanding the complex emotional mechanisms behind the choices and behaviors of the customer during service interactions with the firm.

For this reason, the term *core affect*, which is essential for triggering an emotion, should not be confused with the more generic notion of *affect* (the umbrella term of Bagozzi (1999), mentioned above). Russel (2003) defines *core affect* as a non-reflective and always present neurophysiological state described by the dimensions of *valence* (i.e., positive-negative; pleasure-displeasure) and *arousal* (i.e., activation-deactivation), experienced consciously but generally not directed towards an object or referent. A prolonged state of core *affect* that is often of lower intensity than an emotion and generally without a referent or an object that triggered the state, can be considered a *mood* (Bagozzi et al., 1999; Frijda et al., 1989; Russel, 2003).

For a complete understanding of the emotional terms used, refer to Table 4.

Table 4: Conceptual Background of Emotional Terms

Term	Emotion	Core affect	Affect	Mood	Attitude
Definition	*Mental state of readiness triggered by a change of core affect, often accompanied by a variance of at least one of the two variables of valence and arousal. Emotion is processes by cognition through an appraisal that define the referent (cause) and the assessment (meaning) of this change of core affect. In its phenomenological tone, emotion is manifested through a physiological process often expressed physically (e.g., gestures, facial expressions, posture) and may result in specific actions to affirm or cope with emotions*	*Non-reflective and always present neurophysiological state described by the dimensions of valence (i.e., positive-negative; pleasure-displeasure) and arousal (i.e., activation-deactivation), experienced consciously but generally not directed towards an object or referent.*	*Umbrella term for emotions, moods and attitudes.*	*A prolonged state of core affect that is often of lower intensity than an emotion and generally without a referent or an object the triggered the state.*	*Evaluative judgments, measured by good-bad reactions rather than emotional states.*

For an exhaustive analysis of emotions, the elements related to the process and appraisal cannot be neglected and will be discussed in the next section.

1.3.3 Process and appraisal of emotions (RQ2)

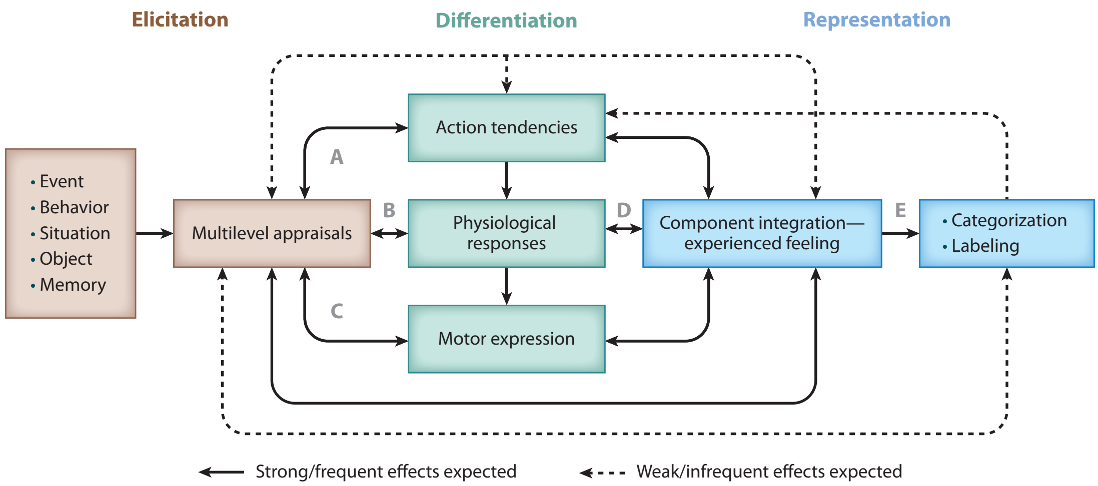
Emotions are nonlinear processes that involve a) the perception of some event (the antecedent event), b) the appraisal of that event in terms of its relevance for the person through elicitation, c) the differentiation and representation mechanisms (Scherer 2009a), and d) the activation of the response components. The response components are influenced by the significance of the emotion for the subject and emotion regulation.

For many authors, such as Mulligan and Scherer (2012), emotion is an interface between an organism and its environment. Different environments may offer different emotions in relation to social contexts and individual's responses and experience. Two concepts are central in this review: *elicitation* via appraisal processes and *differentiation* (Frijda and Scherer, 2009).

In their emotion process, Frijda and Scherer (2009) identified four major functions of emotion, each of which was at a different stage in the process. The first function is the *elicitation* process through which an appraisal of events occurs in terms of their relevance and their consequences in relation to the needs, plans, and values of the person experiencing the emotion. The second function is the *differentiation* process for an appropriate action, able to deal or adapt these events both mentally (in terms of actions readiness or action tendency) and physically (in terms of physiological responses). The third function is the *integration* of information obtained in the elicitation and differentiation processes into a central representation that allows monitoring and representation of the potential responses. The fourth function is, although not always, the *categorization* and *communication* of the emotion episode.

The complete process of emotion according to Scherer and Moors (2019) is represented in Figure 2.

Figure 2: The Emotion Process According to Scherer and Moors (2019).



Source: Scherer and Moors (2019), p.722

Emotions are triggered when a random event occurs. Possible activators of emotions can be external events such as objects (visual, verbal, olfactory), acts of nature, the behaviors of others, and our own actions, or internal events, such as imagination or memories, hormonal changes or drug effects, and finally, voluntary decisions to feel certain emotions. When an emotion is triggered our sensory organs begin to process it through a *multilevel appraisal* (Figure 2).

The stage of emotion elicitation, with the study of the appraisal theories (Ellsworth and Scherer, 2003; Smith and Ellsworth, 1985) and the appraisal-tendency framework (Han et al., 2007; Lerner and Keltner, 2000; Roseman, 1991; So et al., 2015), demonstrates that emotion has a unique set of features that define its kernel (Lazarus, 1991; Lerner and Keltner, 2000; Smith and Ellsworth, 1985). This kernel is named the *appraisal pattern* of the emotion (Han et al., 2007). Appraisal intercepts the change in core affect after an antecedent event has triggered an emotional experience, and the rise of different discrete emotions (Keltner and Horberg, 2015).

The stage of *differentiation* is the first result of the elicitation phase through appraisal and its major response components are motivational action tendency (A), physiological reaction (B), and motor expression (C) that interact with each other. The brain in its central regions represents these interactions in the form of nonverbal feeling (D). The representation of these feelings is categorized and labeled with verbal emotional expression (E) (Figure 2; Scherer and Moors, 2019).

Regarding the multilevel appraisal of emotions (A) in relation to the most relevant variables in firm-customer encounters, an important topic is the evaluation of the mitigation of FLE such as a situational characteristic.

The number of appraisal dimensions varies between six (Smith and Ellsworth, 1985; So et al., 2015) and nine (Roseman, 1996; Van Dijk and Zeelenberg, 2002). These appraisals are used to define discrete emotions but often overlap with the core affect dimensions of valence and/or arousal (Frijda et al., 1989; Ruth et al., 2002). The present work uses the core affect dimensions of valence and arousal and the four appraisal dimensions of emotional experience (i.e., certainty, control, responsibility, legitimacy) to highlight the essential characteristics of the rapport between discrete emotions and the effects of their interaction in firm-customer encounters (Kranzbühler et al., 2020).

Table 5 highlights the contents of the four appraisals of emotional experience and its principal associated discrete emotions.

Table 5: The Four Appraisals of Emotional Experience

Appraisals of emotional experience	**Definition**	**Principal associated discrete emotions**	**References**
1)Certainty	Be certain of the consequences of an event.	-*Anger* is associated with high certainty of negative consequences of an event. -*Fear* is associated with low certainty of negative consequences of an event.	*Lerner and Keltner 2000;* *Smith and Ellsworth 1985.*
2)Control	Have control over a situation or whether it was caused by circumstances.	-*Happiness* can derive both from entity control and circumstantial control. -*Pride* derives only from entity control.	*Keltner and Horberg 2015.*
3)Responsibility	Be deemed responsible for a situation or event.	-*Pride* is associated with the responsibility of own actions. - *Gratitude* is associated with the responsibility of other's actions. - *Anger* derives from an external attribution of responsibility. - *Embarrassment* is related to an internal attribution of responsibility.	*Roseman 1996;* *Keltner et al. 1993.*
4)Legitimacy	Have the perception of own morality in the situation.	-*Guilt* is associated with high legitimacy.	*Roseman 1996;* *Van Dijk and Zeelenberg 2002.*

The present review is based on an analysis of appraisal theories of emotions (Ellesworth and Scherer, 2003; Han et al., 2007; Lerner and Keltner, 2000; Roseman, 1991). In particular, the work of Lench and colleagues (2011) on discrete emotions, has been chosen as it appeared the most comprehensive for this review. They extended the study of discrete emotions from psychology to marketing and, for this reason, expanded from a range of four discrete emotions to ten.

The ten discrete emotions considered by Lench et al. (2011) were:

- Gratitude
- Love
- Happiness
- Pride
- Guilt
- Uneasiness
- Fear
- Embarrassment
- Sadness
- Anger

Discrete emotions have different reactions in relation to physiology, judgement, choice, and behavior (Frijda et al., 1989; Keltner and Horberg, 2015; Lench et al., 2011; Lerner et al., 2003). For example, between anger and fear there are some common aspects and others that are totally divergent. Anger and fear have the same heart rate acceleration, but anger shows higher diastolic blood pressure and hand and head temperature (Roberts and Weerts, 1982; Schwartz et al., 1981). With anger, blood flows to the hands because the person prepares to fight the supervening entity (Ekman et al., 1983).

The *appraisal tendency* framework (Keltner and Horberg, 2015; Lerner and Keltner, 2001) is used to understand when and how discrete emotions have an impact on judgement and behavior related to *pessimistic risk assessment* (Lerner and Keltner, 2000, 2001) due to uncertainty or loss of control. It influences judgement and decision making in two distinct ways: 1) the content and 2) the depth of thought.

Tiedens and Linton (2001) found that the perception of certainty was associated with heuristic processing, whereas the uncertainty is related to systematic processes.

1.3.4 The interaction and change in relevant outcomes in firm-customer encounters and the moderation of emotional connectedness (RQ3, RQ4)

The relevant outcomes considered for this review on emotions are customer's evaluation (Moe and Schweidel, 2011), purchase behavior (Kaplan et al., 1974; Wang et al., 2015; Blom et al., 2017), and sharing behaviors[1] (Berger, 2014; Watson, 2015; Eisingerich et al., 2015). These three outcome categories can be more or less congruent with the appraisals of a discrete emotion. For example, evaluation doesn't need a specific effort or motivation from the customer because it is not a decision and not a behavior. Evaluation isn't associated with a certain risk position. Purchase behavior and sharing behaviors, on the other hand, are related to decision making and associated with an immediate or future action. However, only purchase behavior has a perceived risk position with direct monetary consequences (Kaplan et al., 1974). Sharing behavior is related to social risks of privacy or may not to be perceived as a risk at all (Eisingerich et al., 2015).

Interaction with frontline employees is considered a situational characteristic that can influence relevant outcomes in relation to specific emotions. Emotion is an antecedent of firm-customer emotional connectedness (Pansari and Kumar, 2017; Magids et al., 2015) and customer engagement (Brodie et al., 2011). But little is known about the psychophysiological antecedents of customers' emotion as well as the cognitive process behind emotional connectedness and customer engagement. The cognitive appraisal theory (Scherer and Moors, 2019) defines emotion as an emergent, dynamic episode that involves a continuous change in customers' cognition, motivation, physiological reactions, motor expressions, and feelings to adapt flexibly to relevant service interactions (Figure 2). The elicitation of customers' emotion, and the determination of its characteristics, relies on the subjective, continuous, and recursive appraisal of the service interaction.

[1] In Chapter 3, we have connected these three relevant outcomes with the main customer journey stages. Evaluation is an outcome correlated with the awareness and consideration stages of the customer journey (Lemon and Verhoef, 2016), when customers identify and seek a general solution and become aware of a product or a service (Moe and Schweidel 2011).
Purchase behavior (Kaplan et al., 1974; Wang et al., 2015; Blom et al., 2017) is an outcome correlated to the acquisition stage, when customers buy a product or a service. Finally, sharing behaviors are outcomes linked with retention and advocacy stages, when customers become loyal, advocate and defend the firm (Berger 2014; Watson 2015; Eisingerich et al., 2015).
Research on customer emotions aims to understand how emotional states affect the firm's relevant outcomes such as satisfaction, loyalty, or word-of-mouth and consequently every customer journey stage.

Customers' appraisal of service interaction correlates with their displayed emotions (Mattila and Enz 2002). The cognitive appraisal process results in an emotional episode, characterized by physiological (e.g., skin conductance response), expressive (e.g., facial expressions), and subjective (e.g., feelings) reactions. Since customers' cognitive appraisal is subjective, there is a potentially infinite number of emotions associated with service interactions. The emotional episode is embodied and experienced in a unified way; it being difficult for the customer to consciously establish the distinction between appraisal and emotion, and develop experiential knowledge, skills, and approaches to solve service interaction-related issues (see the somatic marker hypothesis; Damasio, 1996). Afterward, customers can recollect specific emotional episodes, the events that triggered these emotional episodes, the ways in which the emotional episodes are displayed, as well as their normative expectations of frontline employees' (FLEs) response and the observed FLEs' response in that context (Menon and Dubé, 2000). Over the long term, the sensorimotor integration and representation of a customer's emotional experiences in the central nervous system help them to learn about their experiences and to form their action readiness (Scherer, 2009a). Accordingly, a string of positive emotional episodes leads to positive emotional connectedness, approach readiness, and engagement; a string of negative emotional episodes leads to negative emotional connectedness, avoidance readiness, and disengagement.

Positive interpersonal experiences between customer and FLEs favorably influence customers' appraisal of service interactions (Bettencourt and Gwinner, 1996). Emotional connectedness and customer engagement cannot be understood independently of customers' emotions: they are context-dependent and are rooted in the ongoing flow of experiences (Malthouse and Calder, 2011). The cognitive appraisal theory-based definition of emotion also emphasizes that the customers' emotional experiences during service interactions are not only thought about: they are embodied, somatically marked, which strongly determines the long-term valence and intensity of the emotional connectedness and customer engagement with the firm. It is, therefore, necessary to maintain emotional connectedness with customers throughout their journey by means of emotional attachment, social pleasure, and empathy to succeed in the cognitive appraisal checks and elicit positive emotional episodes. For instance, FLEs' prosocial responses to customers' emotions are crucial since emotions refer to personally significant event appraisals that either harm or benefit customers. Customers value FLEs' prosocial responses to their emotions and translate this positive emotional experience by means of empathy into higher satisfaction with the service interaction as a whole (Menon and Dubé, 2000). FLEs' response appraisal is what drives customers' satisfaction. However brief and mundane (Mattila and Enz, 2002) or long and deep (Menon and Dubé, 2000) a service interaction is, customers' positive post-encounter emotions enhance service outcomes and bring benefits to the firm (Lin and Lin, 2011). They positively influence the perception of a professional's performance (Johnson and Zinkhan, 1991), improve the willingness to return and recommend (Tsai and Huang, 2002), and lead to increased satisfaction that is positively related to customers' future behavioral and loyalty intentions (Hennig-Thurau et al., 2006; Jayanti 1996; Lin and Lin, 2011). Emotional connectedness with a service employee is the emotional bond between a firm and its customer that sustains a human, social, interactive experience in service relationships. Although emotional connectedness is not conceptualized as such, it is a necessary principle for the formation of social bonds between firms and customers. It refers to different emotional processes that establish and balance firm-customer interactivity: emotional attachment, social experiences of pleasure or pain, and empathy.

Emotional attachment is a psychophysiological process through which a social bond is established between firms and customers over time (Carter and Porges, 2011). It refers to customers' intimacy toward and need for a sense of belongingness with the firm, not just because the firm performs satisfactorily, but also because it makes the customer feel a certain way (Coulter and Ligas, 2004). Emotional attachment relies primarily on social commitment, which aims at reducing physical distance and thus facilitating the perception and interpretation of physical signals communicated by others, such as facial, vocal, and bodily expressions, smells, and touch. These physical signals are the subject of an automatic, unconscious appraisal, and are interpreted as positive social indicators, such as the opportunity to develop approach behaviors; or negative social indicators, such as the need to develop avoidance behaviors. The physical closeness between firms and customers is therefore important for developing a social bond (Carter and Porges, 2011). It underscores the role of physical interaction between firms and customers to establish an emotional connectedness, which is a strong predictor of satisfaction, customer loyalty, and customer retention (Coulter and Ligas, 2004).

The social engagement that drives the attachment process generates emotional experiences that the customer appraises as a social pleasure (feelings of being listened to, understood, and considered), or as a social pain (feelings of being ignored, misunderstood, and isolated). Social pleasure arises from the feeling of being connected to the firm (Eisenberg, 2016). For example, showing friendliness and presence to customers increases their feeling of warmth and reinforces the feeling of emotional connectedness (Kernbach and Schutte, 2005). Conversely, social pain arises from the feeling of being excluded or misunderstood by the firm and can be expressed through a vocabulary that reflects physical pain (Kasnakoglu et al., 2016). This vocabulary would not only have a metaphorical function: it would describe a real, physical sensation of pain. Indeed, brain imaging studies show that the experience of social pain is based on neural substrates similar to those used in the experience of physical and emotional pain, as well as those used in empathy processes (Eisenberg, 2016). The customers do not only report feelings of social pleasure or pain: they embody them. This embodied experience constitutes a somatic marking of the emotional experience conducive to the development of action readiness (Damasio, 1996). It all depends on the firm's capacity to establish a positive emotional connectedness with the customers in order to understand and feel their emotions and then respond to their requests in an empathic way. During the interaction between a customer and a FLE, this employee may replace the firm as the object in the customer's perception and change the core affect. The emotions that are elicited by holding another entity responsible (such as gratitude or anger) can have a stronger effect on evaluation, purchase, and sharing behavior toward the firm when no interaction with an employee was involved.

Emotional connectedness between a customer and a FLE can produce a new emotional experience and a new change in core affect and this mitigation can realize new behaviors and judgements from the customer, impacting the relevant outcomes and the customer journey.

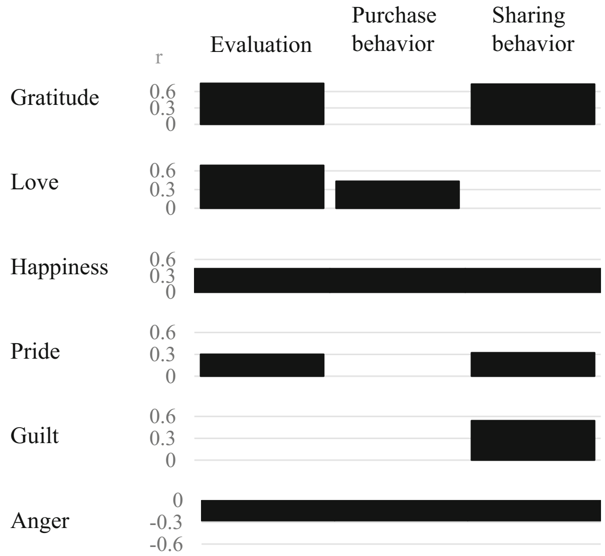
The results of a recent study by Kranzbühler and colleagues (2020), based on a synthesis of 1035 effect sizes, representing 40,777 research participants, provide the varying overall effects for the 10 discrete emotions defined above. In particular, the study shows that positive or negative emotions have stronger effects on human judgement and behavior.

In figure 3, this study demonstrates that there is a larger general average effect size for positive than for negative emotions in relation to the three relevant outcomes. In particular, there are significantly more average effects for *evaluation* and *sharing behavior* than for *purchase behavior* on the level of discrete emotions. In an absolute sense, the positive emotions of *gratitude*, *love*, and *happiness* are the three emotions with the largest impact on firm-relevant outcomes but only *happiness* has an impact on the three relevant outcomes. Consequently, *happiness* has an impact on all the stages along the customer journey. *Gratitude* and *love* are significantly stronger for the *evaluation* stage than for *purchase behavior*. Finally, *love* doesn't impact *sharing behaviors*. No significant effects were found for uneasiness, fear, sadness and embarrassment across any of the three outcome variables. Among the negative emotions, there is only a significant weak effect for *anger.*

Another relevant aspect of the study by Kranzbühler and colleagues (2020) is related to the emotion of *guilt* which would seem to vary significantly depending on whether the customer interacts or not with a frontline operator. This study highlights, moreover, that the effect of *guilt* is significantly different between interaction involving and not involving an employee[2] (Table 6).

[2] This is an aspect to be strongly considered in automated customer service where conversational agents (chatbots) are increasingly used instead of human operators.
Happiness and guilt are the two emotions that this thesis aims to explore across the customer journey. In particular, the idea is to verify with a self-administered questionnaire (see Chapter 4) how customers' behaviors and judgments (in particular customer acceptance of conversational agents or chatbots) change in relation to these two emotions (the first positive and the second negative) in an AI-automated customer journey.

Figure 3: Overall Effect Sizes of Discrete Emotions Per Outcome Variables



Source: Kranzbühler et al. 2020
Note: The height of the bar indicates the strength of effects

Table 6: Moderating Effects of the Interaction with Frontline Employees. Omnibus Tests of Moderation.

Emotion	Interaction		Service recovery		B2B		Product/service type	
	Q (df)	p value	Q (df)	p value	Q (df)	p value	Q (df)	p value
Gratitude	2.437 (1)	0.119	0.336 (1)	0.562	n/a	n/a	0.331 (2)	0.847
Love	0.018 (1)	0.894	0.217 (1)	0.641	n/a	n/a	2.281 (2)	0.320
Happiness	0.095 (1)	0.758	n/a	n/a	0.391 (1)	0.532	1.270 (2)	0.530
Pride	0.349 (1)	0.555	**5.579 (1)**	**0.018**	0.786 (1)	0.375	2.714 (2)	0.257
Guilt	**3.479 (1)**	**0.062**	1.088 (1)	0.297	0.020 (1)	0.886	0.211 (1)	0.646
Fear	0.073 (1)	0.787	n/a	n/a	0.018 (1)	0.892	2.435 (2)	0.296
Embarrassment	0.065 (1)	0.799	n/a	n/a	0.137 (1)	0.711	0.002 (1)	0.967
Uneasiness	0.113 (1)	0.736	**3.019 (1)**	**0.082**	1.935 (1)	0.164	0.496 (1)	0.493
Sadness	0.137 (1)	0.712	n/a	n/a	0.046 (1)	0.831	0.085 (2)	0.959
Anger	0.001 (1)	0.982	0.578 (1)	0.447	**3.227 (1)**	**0.072**	0.116 (2)	0.944

n/a: not applicable due to lack of effect sizes; **bold**: (marginally) significant moderation effects

Source: Kranzbühler et al. 2020.

1.3.5 The management and regulation of emotion according to the EI theories (RQ5)

Literature suggests that EI (Goleman, 1995) is a way to manage emotions during service encounters. Emotions generated during a service interaction tend to affect customer value as well as customer experience. Value creation in a service-dominant logic is a process of co-creation (Vargo et al., 2008).

Service value is a predictor of customer behavior, as the outcome of evaluation precedes emotional responses (Lu et al., 2011). Integrating perceived value with customer satisfaction and perceived service quality, it is possible to explain and predict purchase and sharing behaviors (Tam, 2004).

Many authors argue that emotions are the reason for the development of a strong bond between the customer and the firm and this emotional bond can create a service-profit chain (Homburg et al., 2009).

In relation to the ten discrete emotions observed in service encounters (Lench et al., 2011), there are many effects both on customers and FLE observed in the literature.

Themes like *customer forgiveness*, *revenge,* and *blackmail* or the effects of *demographical factors* have an important role in the management of emotions. Forgiveness is a customer coping strategy after a service failure. The interaction with a human operator is a typical situational characteristic (Figure 5) that facilitates the forgiveness process (Tsarenko and Tojib, 2011). When faced with service failures, customers develop a tendency to take *revenge* (both face to face and behind the back through blackmail) against the firm. Emotional connectedness with a FLE can moderate this effect due to customer reactions of uncertainty and anger (Lerner and Keltner, 2001). Demographic factors can impact the effects of emotions. Appraisals theory confirms that customers of different cultures appraise satisfaction differently. For example, for Asian cultures, a strong relationship dampens the showing of negative emotion (Laroche et al., 2004). Socio-emotional selectivity theory argues that the demographic factor of age may also influence the management of a negative emotion. People tend to regulate their negative emotions better when they grow old, whereas young customers are more impulsive.

Literature suggests employees also get effected by emotions during service encounters. Emotional dissonance during service interaction is stressful. When an employee displays untrue emotions, a state of emotional dissonance occurs and can impact their empowerment (Aziz, 2008). Hostile customer behavior is detrimental to service quality and can cause employee burnout. FLEs are required to alter their behavior to express designed emotion display for value positioning (Sirianni et al., 2013). Similarly, customers have to display self-control during service failure situation.

Emotional intelligence may help control emotional labor and job stress. EI is an intuitive appeal and a predictor of behavior (Robbins, 2013). Emotion regulation is an important aspect of EI (Goleman, 1995) and the amount of research on the topic has grown exponentially in past decades (Gross, 2015a; Koole, 2009). One way to control emotion is to select or modify the emotional experience that would otherwise elicit it. Another is to pay attention in a way that alters the information that becomes available for the emotion-generative process. Alternatively, people can change their appraisal of the emotional experience or their relation to it. Finally, people can directly change the response in their emotional systems (Gross, 2015a; Koole, 2009). There is a large number of antecedents and consequences of emotion regulation strategies such as the goals and motives that initiate emotion regulation (Tamir, 2016), the beliefs that guide emotion regulation efforts (Ford and Gross, 2018), and the decision making that is involved to set a regulation strategy in relation to a particular situation (Sheppes et al., 2014). Emotion generation and emotion regulation are both a cybernetic control process that interface with the environment by perceiving some aspects of it and initiating actions in relation to the valued goals (Gross, 2015a). Emotion generation starts from an antecedent event in the environment, focuses on appraisals of potentially significant stimuli and initiates changes in behavioral, physiological and experiential systems to respond to the situation. This process can give rise to emotional reactions to emotions but not to emotional responses generated through an emotional intelligent labor of the mind[3] (Gross, 2015a).

[3] In Chapter 2, the analysis of emotional and artificial intelligence is declined in a customer service context and the concepts just explored are a useful basis for understanding in practice their meanings and implementations.

1.4 Final Remarks

Understanding the construct of emotions – and the main models associated with them in relation to the main firm-relevant outcomes – is a peculiar topic whatever the interaction tool (human operator or conversational agent) with which a firm wants to equip itself in its frontline strategy.

Before investigating emotional awareness and management tools related to EI (Goleman, 1995) and in order to optimize customer engagement and satisfaction, it was necessary to fully understand the theoretical background relating to the meaning of emotion (Bagozzi et al., 1999), its process, its multilevel appraisals and its categorizations (Scherer and Moors, 2019). The analysis of the literature has allowed us to define a set of 10 discrete emotions (Lench et al., 2011) that are interesting for an automated and omnichannel customer journey, and potentially have an impact on the firm-relevant outcomes during customer service encounters. Finally, the theories on EI have allowed us to re-read the analyzed framework through the correct management of emotional processes. Emotional awareness and emotional regulation are two dimensions of EI that allow for the mediation of the effects of negative emotions and generate new customer emotional experiences during a service interaction without triggering revenge mechanisms from the customer or burnout for service employees.

The results of this literature review suggest that it is valuable to map discrete emotions across the customer journey. Today the customer journey is omnichannel and often automated thanks to different AI-tools. The touchpoints that customers encounter through the entire customer experience are mapping from a satisfaction point of view but in the literature, there is a gap of metrics including affect and, in particular, emotions[4] (Srinivasan et al., 2010).

This thesis highlights the necessity of capturing an emotional map of the customer journey through work on emotional and artificial intelligence. This will allow firms to better understand how to manage customer experience and where there are opportunities to promote or mediate specific discrete emotions. Emotion generation and emotion regulation (Yih et.al, 2019) are a way to influence

[4] In Chapter 3, we define the Emotional Intelligence Framework to create an emotional map of customer journey.

customer action or inaction. Managers should prioritize emotion generation by triggering positive emotions such as happiness over avoiding negative ones, for example with the mediation of a FLE even when the conversation is handled by a conversational agent or chatbot[5].

[5] For this reason, in Chapter 2, we outline a literature overview regarding emotional and artificial intelligence in a customer service scenario.

CHAPTER 2. EMOTIONAL AND ARTIFICIAL INTELLIGENCE IN CUSTOMER SERVICE

2.1 An Introduction to Emotion(s), from a service and system perspective

From a service research perspective, companies and customers interact in an intangible environment with the aim of exchanging their knowledge, skills, and abilities (Vargo and Lusch, 2008a). We argue that emotions and EI are factors to be taken into consideration in order for this interaction to be able to co-create value.

With the advent of AI, in fact, a new paradigm enters the scene for humans, organizations, and managerial studies and new frameworks, models, and techniques are needed to face future challenges of service science (Barile et al., 2016; Barile and Polese, 2010; Bassano et al., 2020). In addition to in-depth analysis of the domain of service (Fitzsimmons and Fitzsimmons, 1994; Grönroos, 2007; Barile and Polese, 2010; Badinelli et al., 2012), these new models have to address individual behaviors and actions (Espejo, 1996; Barile and Saviano, 2013; Saviano et al., 2014; Polese et al., 2016; Bassano et al., 2020; Tronvoll et al., 2017) and research on emotions is the key to understanding what triggers certain behaviors and actions. If the domain of service is strongly based on the relationships between several actors involved in a defined environment, these actors interact on the basis of their emotional experiences and the process of elicitation, differentiation, and categorization of them (Scherer and Moors, 2019). In this line, the construction of service systems requires investigating the ways in which multiple actors with different emotional landscapes build fruitful relationships (Barros et al., 2005; Vargo and Luch, 2008b). With the aim of deepening the emotional dimension of the service system, we carried out a review of the literature regarding emotions and EI during service encounters (Chapter 1).

We argue that the interactions between different actors with different emotional experiences have to be approached from a systemic point of view. The Viable Systems Model (VSM) (Beer, 1984; Espejo and Harnden, 1989; Espejo, 1990; Espejo and Reyes, 2011) and the Viable Systems Approach (VSA) (Golinelli, 2010; Barile, 2011; Barile and Saviano, 2011; Barile et al., 2012a) can further enrich research on emotions by ensuring an understanding of the phenomenon on a broader level. The Viable System Approach (VSA) bases its dynamics on the following concepts: system variation of information (V), categorical values (C) (strong beliefs), and patterns of synthesis (S) (Barile and Saviano, 2011).

Just as the process of acquiring knowledge is influenced by the relationship between categoric values, the structural arrangements and the information units, the process of emotions can also be reinterpreted from the perspective of the informative variety (Barile et al., 2014).

The VSA can frame the whole emotion process in a systemic view by investigating the relationship between components rather than focusing on a specific aspect as many authors continue to do. Nevertheless, scanning the literature reveals that this relationship has only been studied two components at a time, with the exception of the studies of Gentsch et al. (2014) who tried to investigate several components simultaneously.

The antecedent event that triggers the emotion is influenced by the informative variety and the sphere of complexity (Barile et al., 2012a). The interpretation of this complexity, connected to an emotional experience from a system point of view, underlines the radical change in perspective. Multilevel appraisals in an elicitation phase focus on emotions' categories and these categoric values can explain a congenital approach, which is common to every vital system. The emotion process and multilevel appraisals are conditioned by the levels of attention as well as the process of learning. Interactions, in this active or passive variety, come from subjective categoric values, resonant if accepted (positive emotion), dissonant if refused (negative emotion). Consonance and resonance are connected to the concept of the valence of positive and negative stimuli (intrinsic valence) in the emotion process (Barile and Saviano, 2013; Aue and Scherer, 2011).

In the differentiation phase, the interpretation schemes could justify actions tendencies accompanied by physiological responses and manifested in facial, vocal, and gestural expressions, before conscious representation or experience of this changes, categorizes, and labels these changes according to the semantic profiles of emotion words (information units).

The reinterpretation of the emotion process according to the VSA realizes a dynamic view focusing on the factors that trigger an emotion episode in a complex system and drive response differentiation through categoric values in a continuous flow of attention and treating categorization and labeling as information units and optional steps. This new point of view could fill an important gap in the literature by analysing the emotion process not in its entirety but in its individual parts without taking into account the relationships that bind them. A systemic approach to the complex interaction that takes place among customers, firms, and new technologies allows us to define the role of EI and AI in service encounters.

Exploring value co-creation from an ecosystem perspective, in fact, can help us to understand the nature of these complex market relationships. S-D logic identifies actors as co-creators of value, asserts the centrality of resources integration and posits that value is always determined by the beneficiary through actor-generated institution and institutional arrangements (Vargo and Lusch, 2004; 2008; 2016; 2017). Our focus in Chapter 2 is to examine how actors integrate their resources to solve problems and create value from themselves and other actors, by adopting an ecosystem perspective of customer service. The unit of analysis in our case, regarding the interaction among customers, firms, and new technologies, shifts from dyadic encounters to a more complex interconnected of resource integration within a relationship management system. Three elements are important in this ecosystem perspective: 1) *value propositions* that set out attractive offers that prompt interactions, resource integration, and social exchange (Vargo and Lusch, 2008; Wieland et al., 2017); 2) practices that involve interactions that take place in a specific ecosystem context; 3*) institutions* and *institutional arrangements* that set out the social norms (Vargo and Lusch, 2011; Williamson 2000) influencing the nature of interactions and resource integration that relates to value co-creation. In our work, we consider customer relationship management (CRM) as an ecosystem where interactions cannot be considered in isolation because they occur simultaneously, emphasizing the aggregative effect of all interactions among other entities in the system (Vargo and Lusch, 2016) and the characteristic of "interconnectedness" of relationships that are "self-contained" (Lusch and Vargo, 2014: 161). In CRM processes actors and resources are linked together through value propositions, which impact all other resources in the ecosystem. The realization of a "mutual value creation through service exchange" (Lusch and Vargo, 2014: 161) takes place within the customer service. In customer services, in fact, small changes at the micro level may have a profound effect at the mega level (Ormerod, 2011). For example, if in an automated customer service, the chatbot is the first touchpoint with the customer, it must be able to manage every request so that value is not co-destroyed. When the chatbot does not manage the negative emotion and customer complex issue (*micro level*), there can be devastating effects on the sale in online and physical stores (*meso level*), or at the corporate level on the brand (*macro level*) and this could lead to public policy choices (*mega level*) in relation to the adoption of the artificial intelligence tools, not necessarily in line with corporate strategies. In customer service, value co-creation is also bound by institutional structures (routines and rules) that influence and shape the intentions of resource integration (Taillard et al., 2016). For example, some actors may have greater influence in shaping the CRM ecosystem, because of specific social norms that elevate their status. These key actors (Mars et al., 2012) are especially important because other part of the ecosystem may become dependent upon them[6]. These characteristics suggest compelling reason for considering CRM in an ecosystem perspective to understanding value co-creation. They highlight the limitations of traditional dyadic models and consider relationship as systemic, mutually adapting value co-creating interactions. For all these reasons, Chapter 2 highlights the customer service ecosystem in relation to all actors and related resource integration with a specific focus on customer emotions in automated service encounters. In particular, we analyze the literature regarding emotional and artificial intelligence in customer service. Chapter 2, in fact, traces the theoretical background of three different but implicitly connected strands. The first investigates how EI can be used in current customer care scenarios. The second investigates how AI fits into customer service systems through its own conversational agents (chatbots) and robots, triggering an inevitable change. In practice, it underlines the literature on the use of chatbots in customer service interactions. Finally, the third highlights the theoretical framework of customer technology acceptance of these new AI-

[6] In Chapter 4, we will understand the importance of social norms for the acceptance of chatbots because they are included in the model of Wirtz and colleagues (2018) and represent a direct effect for the customer acceptance of service robots.

tools and analyzes the co-creation and co-disruption of value with respect to interactions with human operators.

2.2 The Potential Role of Emotional and Artificial Intelligence in Service Encounters

Engaging customers is important to promote interactivity, collaboration, and value co-creation. Customer engagement is a part of the overall customer experience and the interaction with an "*emotional[ly] intelligent*" customer service along the customer journey (Lemon and Verhoef, 2016) is a way to create customer's fidelity and advocacy. In 1998, Daniel Goleman, in his book *Working with Emotional Intelligence*, explains this interaction thus:

"How customers feel when they interact with an employee determines how they feel about the company itself. In a psychological sense, the 'company' as experienced by the customer is a sum of these interactions. Loyalty is lost or strengthened in every interaction between a company and its customers."

Emotional awareness and emotional connectedness with a customer can make the difference for a firm and customer care operators are trained to work with their EI and connect emphatically with the customer.

Nowadays, service interactions have evolved significantly. Customer service automation (all automated/computerized forms of interaction throughout an omni-channel customer journey) is now an integral part of engagement ecosystems (Breidbach et al., 2014). In particular, intelligent systems such as service robots and conversational agents are gaining popularity and becoming an essential service encounter. They may even replace traditional dyadic interactions between the firm and the customer (Singh et al., 2017; Huang and Rust, 2018; Frey and Osborne, 2017; Oström et al., 2015). However, unexpected side effects may occur and the impacts of intelligent systems on customer engagement are still under scrutiny. This chapter aims to contribute to this question with a strong emphasis on emotion-related issues in firm-customer interactivity.

To date, studies have neglected the notion of emotional connectedness in automated customer service. However, it has been shown that customers become engaged with a firm when the relationship has an emotional connectedness (Pansari and Kumar, 2017). Moreover, several researchers have called for an upgrade of the models that identify how customers use specific service interactions and what are the effects of these service interactions on customer engagement (Lemon and Verhoef, 2016; Malthouse and Calder, 2011). For instance, managing the customer experience across service ecosystems has been identified as one of the most important research priorities among 80 subtopics in service (Ostrom et al., 2015). Others suggested reconsidering the customers' experience throughout their journey and investigating how intelligent systems can mitigate a customer's frustration and anxiety (Lemon and Verhoef, 2016). Finally, the emergence of technology-based service interactions has raised concerns about the optimal balance between "tech" and "touch" in every firm-customer service interaction (Larivière et al., 2017).

2.3 Focus about Emotional Intelligence in Customer Service

The first section of Chapter 2 highlights the literature regarding emotional intelligence (EI) for customer service. In particular, it traces the theoretical background of EI, emotional awareness and emotional connectedness for CRM systems.

2.3.1 What is emotional intelligence?

Emotions, as we saw in Chapter 1, play a fundamental role in our lives (Cohn et al., 2009; Ruvalcaba-Romero et al., 2017). Researchers have found that EI is more important than IQ (Ciarrochi et al., 2001; Goleman, 1995).

In 1989, the psychologist Howard Gardner argued his theory of multiple intelligence (MI). According to Gardner, the notion of intelligence as defined through the various mental tests was limited. Gardner argued that there are multiple intelligences and each one is part of an independent system in the brain. The theory outlines eight types of "smart": linguistic intelligence ("word smart"), logical–mathematical intelligence ("number/reasoning smart"), spatial intelligence ("picture smart"), bodily–kinesthetic intelligence ("body smart"), musical intelligence ("music smart"), interpersonal intelligence ("people smart"), intrapersonal intelligence ("self-smart"), and naturalist intelligence ("nature smart") (Gardner and Hatch, 1989).

In 1990, two American psychologists Peter Salovey and John Mayer defined emotional intelligence "as the ability to monitor one's own and other's emotions, to discriminate among them, and to use the information to guide one's thinking and actions". Mayer and Salovey argued that EI is a cognitive ability, separate but also associated with general intelligence. Specifically, Mayer and his colleagues (2003) affirmed that EI consists of four skill dimensions: (1) perceiving emotion (i.e., the ability to detect emotions in faces, pictures, music, etc.); (2) facilitating thought with emotion (i.e., the ability to harness emotional information in one's thinking); (3) understanding emotions (i.e., the ability to understand emotional information); and (4) managing emotions (i.e., the ability to manage emotions for personal and interpersonal development).

In 1995 Daniel Goleman, an American writer and psychologist, wrote his book named "Emotional Intelligence". For Goleman, EI consists of the ability to recognize, express, and have emotions, coupled with the ability to regulate these emotions, harness them for constructive purposes, and skillfully handle the emotions of others (Goleman, 1995). EI is the quintessential attribute that makes a human being, human. The basic elements of EI are presented using an emotional competence scheme that contains all the important features that affect human life. They are divided into three personal competences (self-awareness; self-regulation; internal motivation) and two social competences (empathy and social skills; see Table 7) (Goleman 1998).

Table 7: Definitions of the Five Competences of EI (Goleman 1998)

PERSONAL COMPETENCES		**SOCIAL COMPETENCES**	
Self-Awareness	Ability to recognize and understand personal moods and emotions, as well as their effect on others	**Empathy**	Ability to understand emotions of other people
Self-Regulation	Ability to control disruptive impulses, to suspend judgment and to think before acting	**Social Skills**	Ability to manage relationships and build networks
Internal Motivation	Passion to work for internal reasons that go beyond money and status (e.g., learning, experiencing, having a happy family)		

Self-awareness

Developing *self-awareness* is the first step to develop EI.

Goleman (1998) recognized that self-awareness is composed of three elements: emotional consciousness, accurate self-esteem, and self-confidence. According to Goleman, self-awareness is the key to social awareness, self-management, and relationship management which are important factors of EI.

Self-Regulation

Self-regulation or self-management is the second step in developing EI (Goleman 1998). Self-management allows strict control of emotional reactions so that people are not driven by impulsive behaviors and feelings. With self-management, it is possible to know flexibility, more extroversion, and at the same time, less stress.

Self-regulation consists of nine key components: (1) emotional self-control; (2) integrity; (3) innovation and creativity; (4) initiative and prejudice to action; (5) resilience; (6) achievement guide; (7) stress management; (8) realistic optimism and (9) intentionality (Goleman 1995; Goleman 2001; Pérez et al., 2005; Fernandez-Berrocal and Extremera, 2006).

Internal Motivation

Internal motivation also plays a key role in EI. People who are emotionally intelligent are motivated by things beyond mere external rewards like fame, money, recognition, and acclaim. Instead, they have a passion to fulfill their own inner needs and goals (Goleman, 1995).

Empathy

Self-regulation is a prerequisite for social awareness. The social awareness cluster contains three competencies: empathy, organizational awareness, service orientation (Goleman, 2001).

Empathy is the most important EI component of social awareness and is directly related to self-awareness. It is the ability to put oneself in another's place (or "shoes"), to understand them as a person, to feel them and to take into account this perspective related to this person or with any person at any time (Ioannidou and Konstantikaki 2008). Empathy means having a deep understanding of different social situations, and effectively modifying the interactions with other people to achieve the best results.

Social Skills

In EI, the term social skills refers to the competences needed to handle and influence other people's emotions effectively; to manage interactions successfully. It is the ability to get the best out of others, to inspire and to influence them, to communicate and to build strong relations and to help them change, grow, develop, and resolve conflict (Adkins, 2004; Gresham et al., 2011). Social skills include influence, leadership, developing others, communication, change catalyst, conflict management, building bonds, teamwork, and collaboration (Goleman, 1995).

2.3.2 Emotional awareness in customer service

Emotionally intelligent service providers have cognition of:

- themselves and their emotions;
- other people and their feelings and what signal such feelings give off;
- the impact they have on others;
- the impact other people have on them.

They are able to use this knowledge to manage difficult conversations with the customer (Goleman 2001).

Every frontline service employee knows that handling multiple customer's queries each day puts them under pressure. It is very easy to take things personally, to become frustrated and stressed. EI helps them to recognize their emotional temperatures and control their effects. Human agents know that the ability to create empathy with the customer is the key to handling customers' issues. Customer service with high levels of EI creates a rapport with customers by speaking their language and showing an interest in what the customer is feeling. In this way, they form better relationships with customers, have more effective results and manage many difficult situations (Goleman, 1998).

2.3.3 Emotional connectedness in customer service

Successful firm-customer interactivity is not only a function of the successful completion of the core service being offered but also a function of the personal aspects of the relationship (Coulter and Ligas, 2004): customers are human beings first (Larivière et al., 2017; Schneider and Bowen, 1999). The social context plays an ongoing, dynamic role in shaping the customers' emotional episode (Menon and Dubé, 2000). Customers appraise interactions throughout their customer journey by means of sociobiological processes that are mainly subconscious, automatic, and emotional. The strength and the direction of customer engagement throughout the customer journey, therefore, depends on emotional connectedness defined as the emotional bond between a firm and its customers that sustains a human, social, interactive experience in service relationships[7]. This empathic capacity (Lajante, 2019), which digital technologies have not yet developed, is an eminently human and emotional process that is essential to the quality of the customer experience.

In dyadic service interactions, empathy plays a central role in emotionally connecting firms and customers. It hinges on FLEs' ability to act upon empathic considerations (Wilder et al., 2014), which refers to a firm's empathic capacity (Lajante, 2019): a voluntary organizational policy intended to develop, maintain, and monitor the ability to share as well as to decode customers' affective and mental states in order to engage them in a prosocial, collaborative, and co-creative relationship. A firm's empathic capacity (Lajante, 2019) stems from the two main components of empathy: the affective component and the cognitive component. The affective component refers to the FLEs' ability to share customers' affective and mental states, such as whether FLEs experience feelings of concern for customers' welfare and are emotionally sensitive to the customers' situation (Gerlach et

[7] See Chapter 1, Paragraph 1.4.

al., 2016). The cognitive component refers to the FLEs' ability to decode customers' affective and mental states, such as whether FLEs accurately identify and understand the customers' perspective (Gerlach et al., 2016). Even if both affective and cognitive components of empathy work mainly on a subconscious level, FLEs' empathic response to customers' queries and concerns is observable: it is the prosocial behavior. FLEs' prosocial behaviors translate into engagement to help customers, support them throughout their journey, and customize the service with a focus on the customers' needs. Customers consciously perceive such prosocial behaviors as empathic concern, which strengthens the emotional connectedness between the firm and its customers.

2.4 Focus about Artificial Intelligence in Automated Customer Service

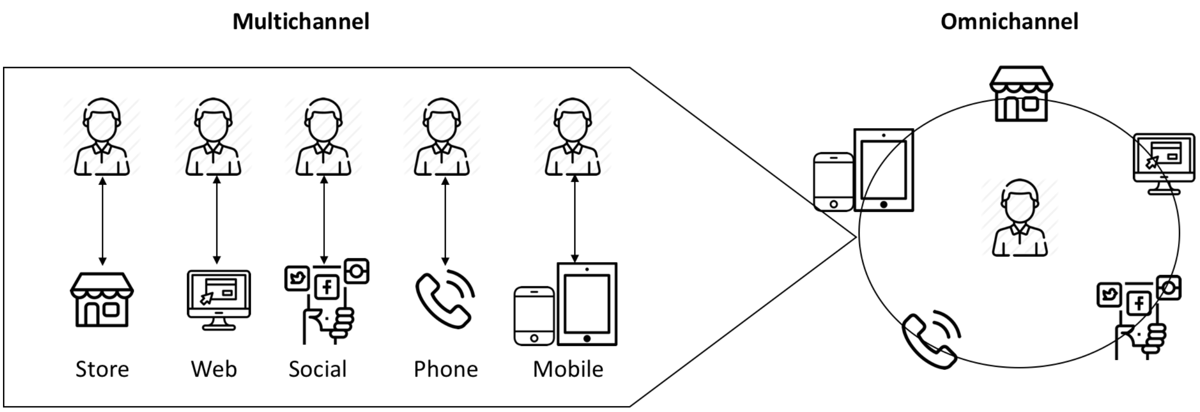
This second section highlights the theoretical background of AI in customer service automation. In particular, it emphasizes that the transformations of customer care systems with the advent of AI are really impressive. This strong impact is evident from an analysis of the literature in relation to agents and service robots. A specific focus was made on chatbots and their ability to read human emotions for a better resolution of issues with the customer. Finally, the section highlights to what extent a chatbot can currently be endowed with EI and how much empathic capacity (Lajante, 2019) is lost in the relationship with it.

2.4.1 How artificial intelligence is changing customer service and the customer journey

The evolution of the customer journey from multichannel to omni-channel (Figure 4), as well as the integration of the intelligent systems in customer service, reshapes service ecosystems and triggers profound changes in customer behavior (Van Doorn et al., 2017; Verhoef et al., 2015). Customers adopt new technologies (e.g., smart mobile devices and social networks) and move seamlessly and interchangeably between various channels to search for information, identify relevant products and services, share opinions and experiences, and talk to the brand (Piotrowicz and Cuthbertson, 2014). In this interconnected ecosystem, customers engage with firms through channels that are easy to access, need-relevant and pleasant for them, whether it is based on a human or automated solution (Lemon and Verhoef, 2016).

Identifying the easiest, need-relevant, and pleasurable channel for engaging customers at the "moment of truth" is therefore a new challenge for firms. In response, they accelerate efforts to deploy and effectively manage the automated customer journey (Grewal et al., 2017; Larivière et al., 2017). The implementation of an automated customer service is perceived as a competitive advantage: it's better at approaching the current market transformation to enhance customer experience (CX) and customer engagement defined as a psychological state that occurs by virtue of interactive, co-creative customer experience with a focal agent/object in focal service relationships (Brodie et al., 2011). Intelligent systems that provide a holistic digital solution across the automated customer journey are one of the key investment areas under CX for all industries (Beatson et al., 2006). As firms pursue their customer-centric efforts and strive to stay close to their customers, technology convergence between intelligent systems and the automated customer journey grows increasingly important.

Figure 4: Multichannel vs Omnichannel Customer Journey

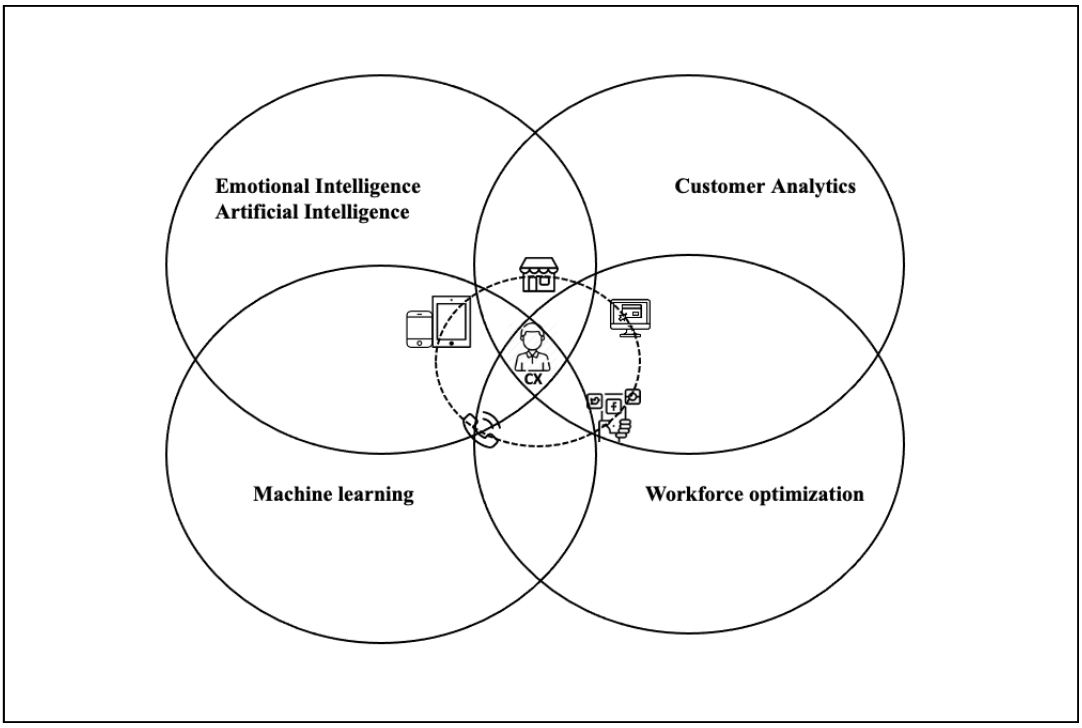


Intelligent systems encompass advanced analytics and learning platforms and process various intelligence inputs that are active across the automated customer journey (Figure 5). They consist of:

- Emotional intelligence – the ability to detect and understand customers' emotions through their omni-channel customer journey. Emotionally intelligent systems can capture real-time customer emotions across channels (voice, chat, e-mail, video), enabling firms to have informed, empathetic conversations with customers.

- Artificial intelligent platforms – “built-in” capabilities to personalize self-service, such as natural language processing, speech recognition, and virtual assistance.
- Machine learning technologies, with advanced self-learning capabilities, help firms to execute next-best actions, such as interactive routing, channel orchestration, and dynamic, real-time campaigns/offers.
- Customer analytics – the process of collecting, integrating, rationalizing, and analyzing data inside or outside organizations, used to deepen customers’ knowledge, describe and predict their behavior, and identify new business opportunities.
- Workforce optimization – a business strategy focused on balancing customer satisfaction, service levels, workforce scheduling, operational costs, and other key performance metrics in order to get the maximum benefit out of the employees at any given time.

Figure 5: Automated Customer Journey and Systems of Intelligence



Among these intelligent systems, service robots and conversational agents such as chatbots represent an affordable, easy-to-implement, and user-friendly AI-solution to strengthen the autonomy and ubiquity of both customers and FLEs (Wirtz et al., 2018).

2.4.2 Agents and robots in service research

In service research literature, the role of conversational agents is still in its infancy, while the debate is richer in the field of robotics and psychology. For the definition, classification, and key features of robots, three kinds of intelligent technologies have been analyzed: 1) conversational agents, 2) social robots, and 3) service robots (Bolton et al., 2018).

Conversational agents or chatbots

Conversational agents have the ability to learn, act, and react. These agents can be divided into embodied or disembodied agents and can perform five main functions to carry out a conversation with the user: a) automatic speech recognition, b) natural language understanding, c) dialogue management, d) natural language generation, and e) text-to-speech synthesis (Griol et al., 2013). *Embodied agents* are able to provide facial expression and body movements, using nonverbal communication (Araujo, 2018), while *disembodied agents* can only interact through message-based interfaces[8] (Holz et al., 2009; Jörling et al., 2019).

Social robots

Social robots are conversational agents with the plug-in of human-like features and the integration of the hardware component. Social robots make consumers feel they are building a relationship with another social entity (Van Doorn et al., 2017). Studies have highlighted four types of social robots: functional tool-like, zoomorphic animal-like, caricatured cartoon-like, and anthropomorphic human-like (Fong et al., 2003; Jörling et al., 2019). Breazeal (2003) defines four classes of social robots in

[8] See Paragraph 2.2.3.

relation to the social model to which they are correlated and the complexity of the interaction scenario (Table 8).

Table 8: Classes of Social Robots and their Description (Breazeal, 2003)

Classes of social robots	Description
Socially Evocative	Robots that have the human tendency to anthropomorphize and capitalize on feelings evoked when humans nurture, care, or are involved with their "creation".
Social Interface	Robots that provide a "natural" interface by employing human-like social cues and communication modalities.
Socially Receptive	Robots that are socially passive but that can benefit from interaction (e.g., learning skills by imitation).
Sociable	Robots that pro-actively engage with humans in order to satisfy internal social aims (drives, emotions, etc.).

Five main elements emerge when robots interact and act in their environment (Table 9) (Fong et al., 2003; Pieska et al., 2013; Čaić et al., 2018).

Table 9: Classes of Social Robots and their Interaction in the Environment

Classes of social robots	Interaction
Socially Situated	Socially situated robots are able to distinguish between other social agents and various objects in the environment (Fong et al., 2003).

Socially Embedded	Robots that interact with other agents and humans and are partially aware of human interactional structures (Fong et al., 2003).
Socially Intelligent	Robots that show aspects of human-style social intelligence, based on deep models of human cognition and social competence (Fong et al., 2003).
Socially Interactive	Robots for which social interaction plays a key role and have human social characteristics (Fong et al., 2003).
Socially Assistive	Robots that provide assistance through social interaction (Pieska et al., 2013; Čaić et al., 2018).

Social robots have many features. They can express and/or perceive emotions, communicate with high-level dialogue, learn/recognize models of other agents, establish/maintain social relationships, use natural cues (i.e., gaze, gesture), exhibit distinctive personalities and characteristics, learn and develop social competences (Fong et al., 2003).

Service robots

From a service-provision perspective, "*service robots are system-based autonomous and adaptable interfaces that interact, communicate and deliver service to an organization's customers"* (Wirtz et al., 2018).

The relevant literature has distinguished between industrial, professional, and personal service robots and devices that require or do not require human input (Thurn, 2004; Vaussard et al., 2014; Murphy et al., 2017).

The idea of robot-as-a-service (Tung et al., 2017) is correlated to the cloud-computing infrastructure and big data (Jordan et al., 2013). From the employee perspective, service scholars have focused their interest on how service robots promise to change the nature of service work (van Doorn et al., 2017;

Wirtz et al., 2018), and on the relationship between service workers and theirs work arrangements[9] (Decker et al., 2017; Subramony et al., 2018).

From the customer perspective, Huang and Rust (2018) highlighted that service robots seem to perform better at managing routines and repeat tasks. Relational services necessitate a stronger human relationship and service robots perform worse because they can't understand, share, and influence people's emotions. However, a more advanced generation of robots is emerging with capabilities in decision making, reading, and adapting to various situations and with the possibility to customize services to individuals like another social entity (Pagallo, 2013; Wirtz et al., 2018). It is interesting to note that the studies of Čaić and other scholars have also recognized the possibility to create a negative value for the customer from the introduction of service robots (Bolton et al., 2017; Čaić et al., 2018; Wirtz et al., 2018). In many cases even if robots can provide a commercial offer that corresponds to customers' preferences and that eliminates search costs, this fact can negatively impact users' sense of decision autonomy, determining resistance to robot suggestions (De Keyser et al., 2019).

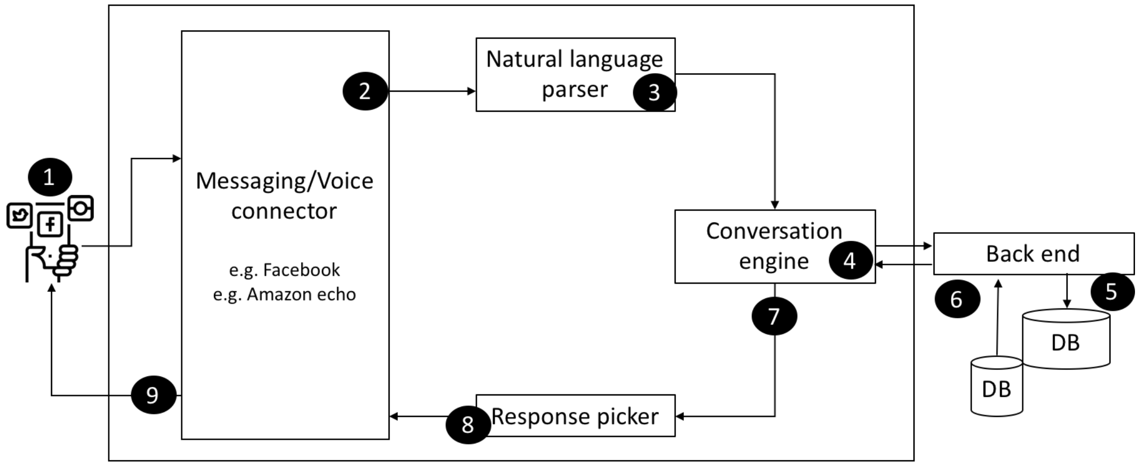
2.4.3 Chatbots and customer service

The attention of this thesis is focused on conversational agents named chatbots. They are frequently used in current customer service systems to manage and resolve many customer inquiries. A chatbot is an AI-powered program that simulates an interactive human conversation by using key pre-calculated user phrases and auditory or text-based signals. A chatbot is also known as an artificial conversational entity (ACE), chat robot, talk bot, chatterbot, or chatterbox. Chatbots contain a text input and output mask, which allows customers to communicate with the software behind them, giving them the feeling of chatting with a real person (Wang and Petrina, 2013). Popular chatbots are calendar assistants (e.g., Rhonda), intelligent assistants that help customers to reserve or to purchase event tickets (e.g., Morph.ai), to search and to buy products online (e.g., H&M), or to book hotel rooms, trips and flights (e.g., KLM). Other fields are chatbots for news (e.g., CNN), weather (e.g., Hi

[9] See Paragraph 2.3 and following.

Puncho), traffic (e.g., Traffic News), and financial chatbots (e.g., Trading Bot). Last but not least, many chatbots are used for customer and service delivery. Whatever the functions associated with it, the term chatbot is mostly used for messenger apps rather than for pure computer programs (AbuShawar and Atwell, 2015). The technical process behind the interaction between a customer and a chatbot can be described in nine steps (Figure 6).

Figure 6: Technical Process of Chatbots (adapted from Dempt, 2016)



In steps 1 and 2, the process starts with a customer's request to a chatbot powered by a messenger app, such as Facebook, or any other apps using text or speech input, such as Amazon Echo. In step 3, a so-called Natural Language Parser (NLP) elaborates the customer's request and translates it into the programming language of the chatbot. In step 4, the chatbot analyses the question and redirects it to the backend. In step 5, several databases (DB) or information systems (IS) connected to the backend give the request to the corresponding query. The chatbot matches the given question with the database(s) in the backend. In steps 6 and 7, once the appropriate result is retrieved from the backend, the chatbot forwards it to the response picker. In the last steps (8 and 9), the chatbot translates the answer in the programming language into the natural language of the customer and sends it to the customer's interface (Dempt, 2016). Chatbots use machine-learning processes to analyze the customers' requests and to answer them as accurately as possible. In addition, some chatbots use the technique of deep learning—a subset of machine learning in AI that has networks capable of learning, unsupervised, from unstructured or unlabeled data (Dempt, 2016).

From the customer's perspective, the perceived technical functionality of a chatbot is not a crucial point to its acceptance: it is rather a matter of social-emotional elements (Stock and Merkle 2018) such as perceived humanness (Tinwell et al., 2011), perceived social interactivity, and perceived social presence (van Doorn et al., 2017). However, a chatbot isn't an emotional bot that could detect negative emotions to manage difficult conversations. From this perspective, subjectively experienced aspects of the automated customer journey related to affect-laden events must be taken seriously, at least as much as the objectively observable string of touchpoints. First, customer experience relies heavily on emotions that influence perception including their overall satisfaction with the firm (Mattila and Enz, 2002) and decision-making through the customer journey. Second, examining the emotional content of the customer's experience can enhance the understanding of customer satisfaction and engagement (Price et al., 1995). This will, in turn, help to go beyond what customers "want" and go further in understanding "why" customers want it at a specific stage, i.e., the emotional motivators (Magids et al., 2015).

Pros and cons of chatbots

The pros and cons of chatbots are defined in terms of functional needs and social-emotional needs (Heerink et al., 2010).

Pros. Thanks to chatbots, firms have new paths to interact with their customers through one-to-one communication. Whereas previously, customers would have to go to a website and browse for a long time to find the right information, chatbots handle customers' service inquiries in a straightforward and efficient manner. Usually, customers use the messenger apps for private purposes and firms can enter this private communication channel in their CRM strategies. Accordingly, chatbots allow customers to get in contact with firms whenever they want to, without paying attention to time zones, opening times, and waiting loops of call and service centres. Chatbots are very promising for international and/or digital firms.

Additionally, the direct interaction with customers helps firms to know their customers and their preferences in a new way. Often, customers link their social media profiles with their messenger profiles, which offers firms direct access to customers' interests, responses, and profiles. A chatbot collects necessary information or questions during conversations with customers. In addition, the chatbot stores individual customer preferences based on the customers' requests, purchase history, and other consumption-related activities. These new data sets give firms the opportunity to address their customers in a relevant manner: customized offers can be targeted directly and personally to customers.

Cons. In contrast to the benefits of chatbots, firms should be aware of the risks associated with this AI-powered technology. An important topic is customers' data protection. Communicating with customers, firms collect and store as much data as possible to use for further marketing. Customers need to know that firms' chatbots and messenger platforms collect personal data. If firms offer a stand-alone chatbot app, they are responsible for protecting and handling customer data adequately. However, if firms offer their chatbot on a third-party platform, data is also sent to operators and platforms like Facebook: thus, firms should ensure both data privacy and data protection. Otherwise, customers', as well as public organizations', trust toward the firms might be severely damaged (e.g., see Facebook-Cambridge Analytica Data Scandal).

Consumer acceptance also depends on how well a chatbot can deliver on the functional needs (Heerink et al., 2010). According to the technology acceptance model (TAM; Davis, 1989), a customer's intention of using a chatbot depends on the cognitive appraisal of its perceived usefulness and ease of use. However, customers' queries and complaints are sometimes tricky: chatbots could be inefficient at providing adequate answers to specific issues. For instance, if customers repeatedly ask the same questions without getting relevant answers, the chatbot loses credibility and customers will soon break off the communication and will not use the chatbot anymore (Braun, 2003). Such situations raise another important issue: a chatbot doesn't empathize with customers. When it is necessary to manage a disservice or to respond to customer needs for assistance, the empathic capacity of human operators is functional to establishing an emotional connection with customers in order to avoid an escalation toward the loss of trust in firms (Wieseke et al., 2012). But a chatbot is not endowed with such EI; it is not able to respond pro-socially to a customer's anxieties by customizing the service. It is, therefore, necessary for a chatbot to be endowed with EI in order to detect customer emotions and to warn human operators that a traditional, dyadic interaction is required to respond appropriately to the customer's complaints.

To sum up, customers are likely to adopt chatbots if not only perceived functionality but also social-emotional elements, are present through the automated customer journey (Heerink et al., 2008; van Doorn et al., 2017). So far, chatbots help customers resolve simple problems in an always-on modality. But they can't connect emotionally and empathize with them. However, emotional connectedness (Pansari and Kumar, 2017) and empathy are fundamental in firm-customer interactivity (Drollinger and Comer, 2013; Gorry and Westbrook, 2011; Lee et al., 2011; Parasuraman et al., 1985; Zeithaml et al., 1996). On the contrary, a lack of empathy or an inability to connect emotionally with customers due to technical limitations might dramatically impair customer acceptance of automated service interactions such as chatbots and then damage customer engagement over time[10] (Abbasi and Alvi, 2013; Agnihotri and Krush, 2015).

2.5 Focus about the Customer Perspective on Chatbots vs Frontline Employees

The third section of this chapter highlights the literature regarding the customer perspective on chatbots vs FLEs. In particular, it traces the theoretical background of TAM (Technology Acceptance Model) and the other models for acceptance of, and resistance to, technologies by customers.

[10] In Chapter 4, with a cross-sectional design research structured with a self-administered questionnaire, we analyzed the influence of the social, relational and emotional aspects on customer acceptance of chatbots.

Customer differences and situational characteristics in the preference for chatbot/human agent interaction are mentioned and a focus has been dedicated to value co-creation and co-disruption in human-like interactions in customer service. This third section ends with a question about chatbot and human labor: substitution or cooperation?

2.5.1 TAM, UTAUT and sRAM

Understanding why and how customers accept or reject new technologies is certainly a very important point of discussion for firms.

The Technology Acceptance Model (TAM; Davis, 1989), in reference to the workplace context, highlights that *perceived usefulness* and *perceived ease of use* impact the adoption and use of information technology. The first extension of TAM, elaborated by Venkatesh and Davis (2000) and known as TAM 2, related perceived usefulness to the processes of social influence (subjective norms, voluntariness, and experience) and cognitive instrumental processes (job relevance, output quality, result demonstrability, and image); furthermore, TAM 3 (Venkatesh and Bala, 2008) included experience as a mediator of ease of use that functions through the mechanism of anchoring and adjustment.

To better understand how consumers embrace new technologies, other models have been advanced by incorporating different elements into TAM. For example, the unified theory of acceptance and use of technology (UTAUT; Venkatesh and Davis, 2000) is based on four predictors of users' behavioral intention (Table 10).

Table 10: UTAUT Model and the Four Predictors (Venkatesh and Davis, 2000)

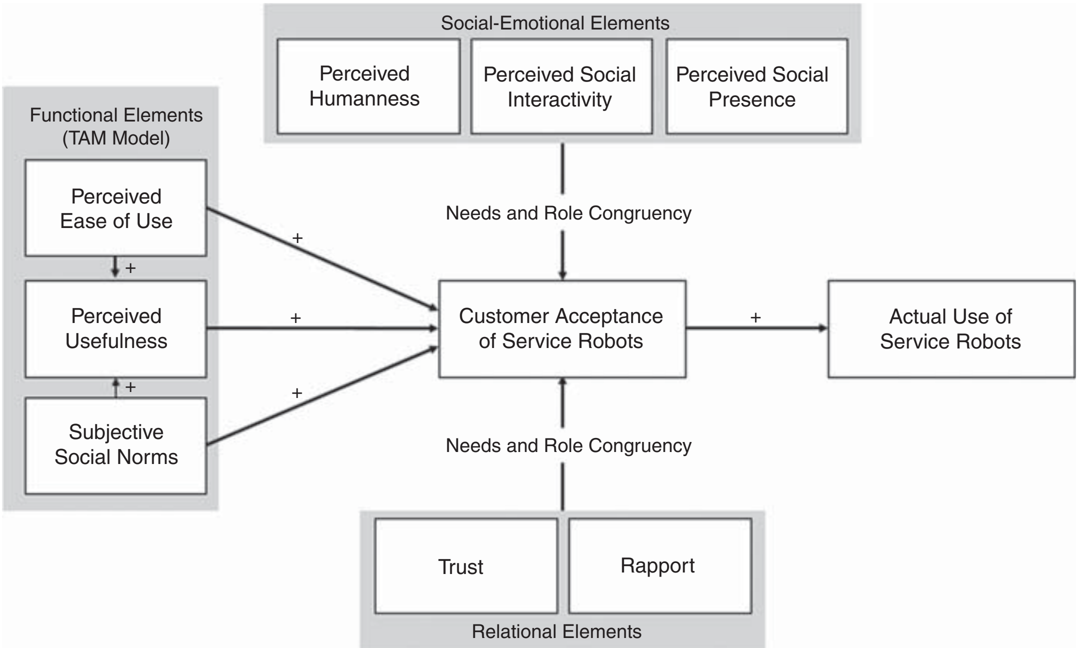
UTAUT Predictors	Description
Performance expectancy	The degree to which an individual believes that using the system will help them to attain gains in job performance.
Effort expectancy	It is defined as the degree of ease associated with the use of the system.
Social influence	It is defined as the degree to which an individual perceives that important others believe he or she should use the new system.
Facilitating conditions	They are defined as the degree to which an individual believes that an organizational and technical infrastructure exists to support the use of the system.

UTAUT 2 included three additional constructs (i.e., hedonic motivation, price value, and habit), stressing the role of experiential and hedonic aspects of technology. In the model, an important role is given to *individual differences* (i.e., namely age, gender, and experience) that can mitigate the effects of these constructs. The unique critique of these models is their tendency to focus on acceptance without considering the reasons for resistance. In particular, Kleijnen et al.'s (2009) identified that *resistance*, *rejection*, and *postponement* are the three main aspects of customer resistance.

Čaić et al.'s (2018) studies highlight a new form of human-like interaction that emphasis human-centred experiences with users. In human-like interactions, users' expectations are higher (Wirtz et al., 2018) and service robots have to understand users' mental models to strongly influence people's expectations (Kiesler and Hinds, 2004). The work of Wirtz et al. (2018) is fundamental to understand every variable that can influence users' acceptance of robots. Their sRAM (Service Robot Acceptance Model), in fact, is a new conceptual model that explores the customer's intention to use or adopt service/social robots and conversational agents during a service experience. The sRAM differentiates among *functional* (perceived ease of use, perceived usefulness, subjective social norms that are in the

TAM model by Davis et al. (1989)), *socio-emotional* (perceived humanness, perceived social interactivity, perceived social presence), and *relational* (trust and rapport) elements (Figure 7).

Figure 7: sRAM Model by Wirtz et al. (2018)



The sRAM model adds two new elements to the TAM model. The first is represented by the social-emotional dimension and the second by the relational dimension. The social-emotional dimension demonstrates that customers' acceptance of robots depends on perceived humanness (Tinwell et al., 2011), perceived social interactivity and perceived social presence (van Doorn et al., 2017). The relational dimension in an interaction with a service robot considers the trust and rapport variables (Heerink et al., 2010; Nomura et al., 2006) as the perceived competence and benevolence (trust) and the perceived enjoyable experience (*rapport*).

2.5.2 Customer differences and situational characteristics in the preference for chatbot/human agent interaction

A customer's personality and their situation determine the success of an interaction with a firm and not only service improvements (Bettencourt et al., 2013).

Osburg et al. (2017) discuss the person-situation interaction approach, in which the characteristics of a situation interact with the characteristics of an individual. If both characteristics are in favor of the service encounter, synergistic effects may even occur. Practically, the value for customers of a technologically-enabled service encounter emerges from situational as well as individual characteristics (Kumar and Telang, 2012; Scherer et al., 2015).

A customer's preference for interaction with chatbots vs human employees depends on the following characteristics, amongst others (Dabholkar, 1996; Simon and Usunier, 2007):

- Rational (economic efficiency), optimistic, innovative, and technologically-ready customers prefer a chatbot interaction.
- Emotional, dependent on personal recommendation, and technologically-anxious customers prefer an interaction with human staff.

Table 11: Predictors of Customer Preference: Chatbot vs Human

Predictors	Customer Preference
Nature of enquiry	Chatbot is good at managing simple enquiries, for complex task or trouble issues human staff is preferred by customers.
Urgency of the enquiry	Chatbot can manage urgent simple tasks while human staff is superior to solve problems without time pressure.
Customer relationship	Customer relationship is better supported by the human connection that transforms empathy with human staff into trust. For new customers chatbots can facilitate a first interaction and relationship with the company.

Rational vs emotional personalities have different approaches along their customer journey and the importance of their interaction with the situation becomes clearer. At the beginning of the customer journey, customers are attracted by emotional aspects while at a later stage when the novelty effect wears off, they pay attention to rational/functional aspects (Colliers and Kimes, 2013).

The three main situational characteristics that highlight if a customer may perceive chatbot or human staff as superior are described in Table 11 (Fornell et al., 1996; Kumar and Telang, 2012; Ravindram and Kumar, 2015; Scherer et al., 2015).

2.5.3 Value co-creation and co-disruption in human-like interactions in customer service

An interaction with a chatbot or a service robot does not always lead to value co-creation for a company. In particular, when a chatbot completely replaces human staff, it could be possible to co-destroy the value, as demonstrated by the studies of researchers like Čaić et al.'s (2018).

In fact, Čaić et al.'s (2018) research demonstrates that human-like robots that interact with customers on a social level, for example with facial and voice recognition technology (van Doorn et al., 2017), have both a capacity to co-create and co-destroy the value because if service providers hope to encourage customers in a new and innovative service scenario, they have to considerate the value networks in which these customers interact. A new service can have a disruptive nature throughout the value network. To understand this dynamic, a network conscious approach to technology-enabled services is needed (Chandler and Lush, 2015).

When service beneficiaries consider innovations, they evaluate how the value co-creation/destruction trade-offs impact not just them but any other actor in the network. In the definition of value networks, there is an important link with network actors as a fundamental asset for innovating the design of service systems (Bassano et al., 2020). The mapping of systems (Patricio et al., 2011) and network (Tax et al., 2013) visualizations often excludes service beneficiaries and it is focused on the structure and flow of goods, information, or money (Briscoe et al., 2012), rather than value co-creation. For this reason, service managers have to focus on a value network perspective (Bassano et. al, 2020) when they introduce complex robotic solutions and capture service beneficiaries' understanding of value co-creating networks or engage different actors for the realization of value.

2.6 Final Remarks

Emotional intelligence is a very important asset for customer engagement along an omnichannel customer journey. Knowing the customer's feelings and emotions at every touchpoint can make a real difference. The emotional connection that the customer establishes with the firm appears fundamental to create loyalty and advocacy. The contact center is certainly a relevant touchpoint and today, in many large companies, operators are trained to connect empathically with the customer.

With the advent of AI and the use of service robots and more particularly of chatbots, firms often lose their empathic capacity (Lajante, 2019) and this situation could create a co-destruction of value. It appears that this problem can only be avoided if the chatbot is used for simple questions to resolve immediately. For much more complex problems, it is inopportune not to use the human operator because the chatbot today does not have an advanced emotional reading (emotional awareness) of customer feelings, nor an empathic ability to motivate and engage him.

Chapter 2 intended to define the theoretical background relative to the themes of emotional and artificial intelligence applied to customer care systems. In particular, the first part defined the literature relating to EI, framing it in customer care systems and in an omnichannel customer journey. The second part looked into the deep changes in service science that occurred with the introduction of AI algorithms and explored the theoretical definitions of conversational agents and the main service robots. Finally, the third part of the chapter outlines the elements that impact the customers' acceptance of these new tools and the possible value co-creation or co-destruction.

The theoretical approach taken in Chapters 1 and 2, is used in Chapter 3 to define an emotional map of the customer journey through a combination of emotional and artificial intelligence for automated customer service. This emotional map is synthesized in our EAI framework. The EAI framework is able to allow the dialogue between EI of FLEs and AI of chatbots to fully engage the customer in an automated and omnichannel customer journey.

CHAPTER 3. EMOTIONAL ARTIFICIAL INTELLIGENCE-POWERED CHATBOTS: A NEW CONCEPTUAL FRAMEWORK FOR CUSTOMER SERVICE

3.1 Emotions and AI-Powered Chatbots

AI is radically transforming customer service, with AI-powered chatbots playing the FLEs' role. Programmed to speak or write like a human, chatbots are poised to usher in a frontline service revolution.

While early chatbots were designed to resolve simple request clearly and concisely, chatbots 2.0 are programmed to be "perfectly imperfect" in their imitation of humans (Byrne, 2018). As a result, a reported 50% of customers who have interacted with a chatbot are unaware their frontline agent was non-human (Hyken, 2017b). As explored in Chapter 2, the advance of humanlike AI creates a loss of empathic capacity if the firm doesn't manage customer emotions on par with an interaction with a human operator. However, research on the impact of chatbots, in a traditionally human-to-human service encounter is at an early stage. Additionally, little research has investigated how chatbots affect customers in the dyadic service encounter. More research in this area is needed because today chatbots are a frequent AI-tool in customer service and customers' emotional distress, need for assistance, and critical/sensitive periods (e.g., anxiety, frustration, lack of trust) are serious issues for firms who want to succeed in connecting emotionally and empathize with customers to enhance the customer experience.

In exchanges characterized by high affect, perception of risk, personalization, long duration and/or intimate interaction, customer needs of FLEs' signs of attention and assurance may be difficult to replace with a chatbot. One such example is a medical or legal service in which customers need a FLE's interaction for their knowledge and expertise to confidently evaluate the service (Patterson, 2016). Similarly, for services in which empathy and care for customers increase customer satisfaction (Webster and Sundaram, 2009), chatbots may be an unsuitable FLE replacement. Furthermore, for emotionally charged service encounters a human operator may reflect empathy and emotional connectedness toward a customer who might feel discomfort, insulted, or offended (Dallimore et al., 2007; Rafaeli et al., 2017), given that emotionally charged service encounters require FLEs to display authentic positive or negative emotions to satisfy customer needs for understanding. Here, customers may perceive that the affect conveyed by chatbots to be insincere and artificial. Customers expecting a relationship with FLEs (Scott et al., 2013) welcome facial expression (Lee and Ching Lim, 2010; Lim et al., 2017), and look for aspects of non-verbal communication to reduce ambiguity (Hennig-Thurau et al., 2006; Patterson, 2016; Söderlund and Rosengren, 2008), feel comfortable (Lloyd and Luk, 2011), build trust (Gabbott and Hogg 2001; Sharma and Patterson, 1999), and develop rapport (Gutek et al. 2002; Medler-Liraz 2016). Although AI technology can outperform humans in reliability and accuracy (e.g., task-related aspects) (Meuter et al., 2005), it may lack rich communication (Miyazaki et al., 2007) and emotion (Grougiou and Pettigrew, 2011). The absence of these distinguishing characteristics of interhuman interactions may have adverse results on customer perceptions of trust and feelings of comfort during the service encounter (Gabbott and Hogg, 2001). For these reasons, knowing when a human operator is required to manage a difficult interaction appears to be fundamental. In this third chapter, we argue that firms must identify customers' negative emotional episodes and need for assistance in order to switch from the automated (AI-powered chatbots) to the traditional (human operators) customer service at the right time (Lajante and Del Prete, 2020). Finding this switch point, in the case of a difficult emotional conversation, means having more symbiotic interactions, engaging customers in a collaborative way, and avoiding the loss of the firm's empathic capacity (Lajante, 2019). Accordingly, intelligent systems such as chatbots should be artificially endowed with EI to monitor customers' emotional episodes throughout the automated customer journey and redirect them, if necessary, to an empathic, human-based service interaction. We argue that chatbots do not need to impersonate humans[11]. To provide customers with superior experiences they should quickly deliver responses that speak directly to their needs, and they should continuously learn so that, over time, they are able to apply meaningful responses to unique requests.

[11] In Chapter 4, we demonstrate the significance of this statement empirically.

Moreover, chatbots need not have the empathic ability to establish an emotional connectedness with customers. Rather, they should be aligned with customers motivations and social expectations to strengthen emotional connectedness and customer engagement. Accordingly, chatbots should be able to evaluate the service interaction in real time so as to recognize when there is a variation in the customer's motivations and his or her issue becomes more complex. As such, chatbots should develop the ability to read emotions in order to identify the exact point at which the conversation must be managed by a human agent. We define this emotional capacity as Emotional Artificial Awareness (EAA) and we argue that this feature could be built by adding a Sentiment Analysis Algorithm (SAA) to the chatbot's normal technical process (NLP). The SAA works to identify customer emotional states through various textual conversations. When customers' emotional states are neutral or positive, the chatbot proceeds with the request. When negative emotional states are detected, to avoid escalation, chatbots diverts the conversation to a human agent, thereby preventing a loss of emotional connectedness and co-destruction of value in the omnichannel customer journey[12].

3.2 Emotional Artificial Intelligence (EAI)

We argue that to fully engage the customer a chatbot should incorporate a cognitive and an emotional dimension. The cognitive dimension, which is more technology-oriented, utilizes machine-learning programs to analyze customers' requests and to answer them as accurately as possible[13]. This cognitive dimension, as we saw in the second chapter, is represented by functional elements of the sRAM of Wirtz et al. (2018). The emotional dimension, principally emotional awareness[14], which is still challenging in the current state of technology, could enable chatbots to identify customers' emotional episodes and work accordingly in order to switch to a human operator when a complex issue arises (Lajante and Del Prete, 2020). A human operator may display empathetic concern, share

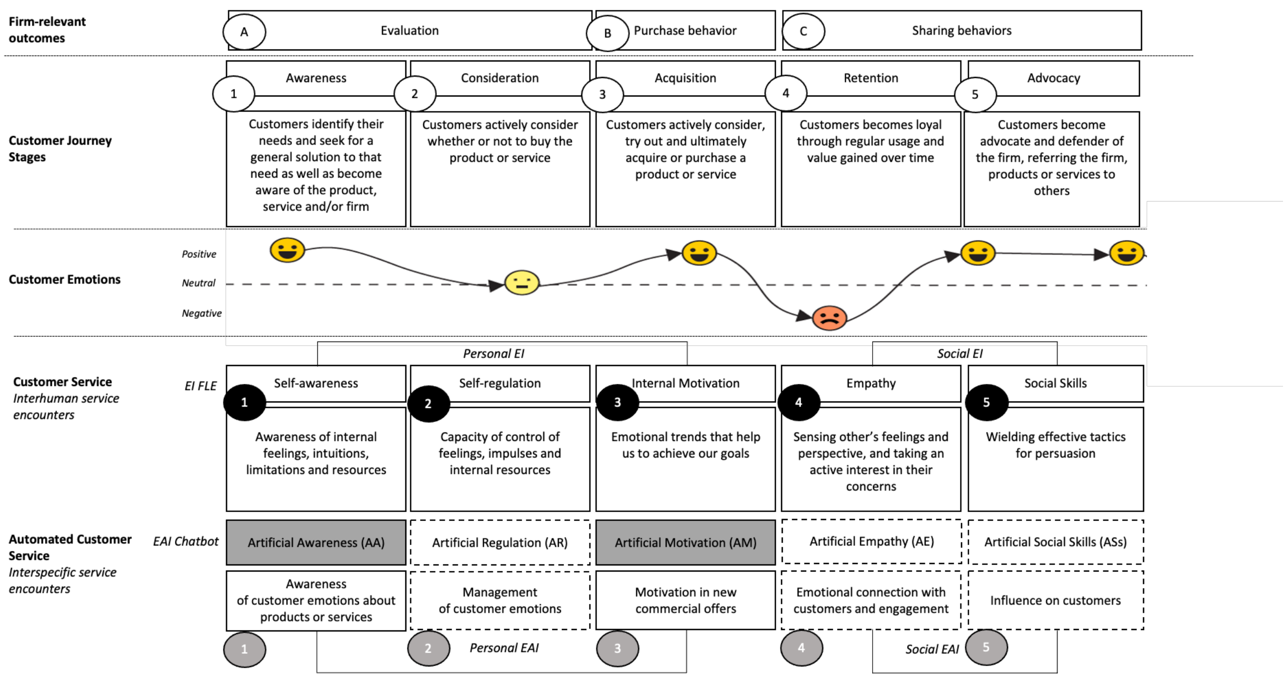
[12] See Chapter 2, Paragraph 2.5.3.
[13] See Figure 6, Chapter 2.
[14]In Chapter 4, Emotional Awareness is considered, in our empirical framework, a moderator effect of the sRAM by Wirtz et al. (2018).

customers' feelings, and establish an emotional connectedness: this is the prerequisite for a genuine prosocial response.

The incorporation of EI dimensions in AI-powered chatbots is necessary to create "rapport and trust" in customer acceptance of AI-technologies (Wirtz et al., 2018). For this reason, this thesis introduces the concept of emotional artificial intelligence (EAI). Specific EAI algorithms (in particular artificial awareness and artificial motivation) could allow the chatbot to recognize customers' emotions during the customer journey and motivate customers when they display positive emotions or divert the call to a human operator when they display negative emotions.

In Figure 8, we have drawn an emotional map of the customer journey. The emotional map explores the three firm-relevant outcomes from the points of view of discrete emotions (explored in the first chapter), customers emotions, FLEs' EI in an interhuman service encounter, and what we have named chatbots' EAI in an interspecific service encounter. In doing so, we have accepted the request for more research in this area by Kranzebulher and colleagues (2020) and Robinson and colleagues (2020).

Figure 8: Emotional Artificial Intelligence in Automated Customer Service



We argue that interhuman service encounters will continue to be extremely important because many service exchanges require a conventional customer-FLE interaction (Liao and Chuang, 2007). However, chatbots are increasingly used instead of human operators, so this poses several problems where the interaction is not very effective due to an inability to read customer emotions.

We argue that in order for the chatbot to completely replace the human operator, all five dimensions of EI should be considered as additional components of AI. This scenario appears futuristic and still far off but research is evolving in this sense. So, we argue, thanks to the literature review carried out in the first two chapters, what competences these components of EAI should have and that a chatbot should be equipped with to operate autonomously.

The first plug-in is *Artificial Awareness*. This emotional competence could endow AI-powered chatbots with the ability to identify customer emotions along an automated customer journey. In the context of conversations with a chatbot, artificial awareness could hinge on emotion identification from text, a recent field of research closely related to sentiment analysis. Sentiment analysis aims at identifying positive, neutral, or negative feelings from text (dimensional approach of emotion) as well as identifying emotional content through the expression of texts (categorical approach of emotion) (Shivhare and Khethawat, 2012). The emotion identification process of artificial awareness starts with the two stages of *detection* and *adaptation* and is a prerequisite for a chatbot to interact with customers. Although emotion identification is automatic for humans (Adolphs, 2002), it is still a challenge for chatbots. This process needs different elements (hardware and software) to detect feelings, moods, and affects[15] and understand human emotional behavior. For instance, sensors' data might feed the chatbot database with emotion-related physiological information. Afterward, applying an artificial awareness algorithm in interspecific service encounters (Robinson et al., 2020) would help to analyze and use the emotional content to connect with customers and recognize their emotions at the early stages of the automated customer journey – the stages at which the customers

[15] See Table 4 in Chapter 1.

acknowledge that they have a problem or a need to fill. Customers start by conducting a very broad search and simply look into what options are available. By appropriately recognizing customer emotions during the awareness stage, a chatbot with artificial awareness could activate the push on blog posts, social media content or video ads to engage customers or switch the call to a human operator if there is an escalation of negative emotions with the customer (Lajante and Del Prete, 2020). The artificial awareness algorithm could also endow the chatbot with a capacity to discern the valence and arousal[16] of the customer's emotions and allow the same, in the case of managing complex problems, to divert the call to a human operator.

The second plug-in is *Artificial Regulation*. This emotional competence could endow AI-powered chatbots with the ability to manage difficult emotions. Once customers recognize they have a problem to solve, they start to evaluate their options. Options evaluation could cause negative emotions such as anxiety or frustration and an artificial regulation algorithm could manage customers' negative emotions and mitigate them with three distinct components: reflection, acceptance, and integrity. Reflection helps to reflect on customers' negative emotion to identify the problem. Acceptance helps to observe the problem as it appears and seek the right solution. Integrity helps to select the relevant option and transform customers' negative emotion into motivation.

By managing the customers' negative emotions, a chatbot powered by an artificial regulation algorithm could gently persuade the customer to take a closer look at the new products or services and to consider them a viable option. Content, such as comparison charts, demonstrations, case studies, and product guides could help to support customer engagement during the consideration stage of the automated customer journey. At this stage, no AI-powered FLE has the ability to mediate customer emotions as a human operator would do, so research on this type of emotional competence could enrich knowledge in the scope of service science. To date a chatbot is not yet able to take the place of a human operator in the management of customer negative emotions, therefore in this thesis,

[16] See Chapter 1, Paragraph 1.2.1 and 1.2.2.

we support the collaboration between AI-powered FLEs and human FLEs and not the autonomous management of the customer by the chatbot.

The third plug-in is *Artificial Motivation*. This emotional competence could endow the AI-powered chatbots with the ability to motivate customers in purchasing products and services. Motivation refers to “the reason one has for acting or behaving in a particular way” (Goleman 1995) and is a relatively new idea in AI-powered intelligent systems. Applied to the EAI model, computational models of motivation are combined with models of reinforcement learning (Sutton and Barto 2000) from the field of machine learning to develop chatbots that can adapt to new problems by learning. In particular, artificial motivation hinges on three components that reflect different stages of information processing (Neisser, 1967; Norman, 1998): *perception*, *cognition*, and *action*. First, customers’ emotions are perceived and recognized. Second, the optimal actions are determined regarding the current situation, ongoing tasks, and goals. Finally, a selected action is prepared and executed. Artificial motivation could be the component that helps chatbots to suggest products or services relevant to customers’ emotion at the acquisition stage of the automated customer journey. Here, customers have already acknowledged that they have a problem or a need to fill and have explored their various options. Options are narrowed down and customers are now ready to make a purchase decision. This third stage of the automated customer journey is at the bottom of the sales funnel and is one step closer to transforming the prospective customer into a paying customer. This is the stage at which a chatbot powered by an artificial motivation algorithm could engage with customers and showcase why they should purchase products and services. Chatbots powered with an artificial motivation algorithm could show customers what makes products or services stand out from principal competitors by means of testimonials from previous customers and in-depth case studies, thereby utilizing the perception and cognition components of artificial motivation. Moreover, chatbots powered with an artificial motivation algorithm could offer a free trial or a more in-depth demonstration, so customers get a better understanding of what the firm has to offer. This is the action component of artificial motivation.

The fourth plug-in is *Artificial Empathy*. This emotional competence could endow the AI-powered chatbots with the ability to share as well as to understand customers' affective and mental states to engage them over the long term, into the post-purchase stage. Empathic concerns are important in social interactions, especially when a need for assistance is identified.

In our analysis, supported by literature on EI, artificial empathy should consist of three principal components: *contagion*, *connection*, and *compassion*. Contagion could be an evolutionary precursor that enables social robots and conversational agents to share customers' emotional state – the affective component of empathy. Connection could be the capacity to connect emotionally with customers. Compassion is the faculty of an artificial empathy algorithm to understand what customers feel – the cognitive component of empathy – and participate with their emotions to engage them at the retention stage of the automated customer journey. An artificial empathy algorithm could make customers loyal by means of prosocial responses and customer loyalty programs to boost customer retention over the long run.

To date, a chatbot is unable to have its own empathic capacity, so we argue that complex calls should be diverted to a human operator who will use their empathy to emotionally connect with the customer and mediate the emotion.

The last plug-in is *Artificial Social Skills*. This emotional competence could endow the AI-powered chatbots with the ability to engage customers to advocate products, services, and more broadly, the firm. Customer advocacy is action toward other customers. It draws insights from the voice of customers and turns them into recommendations that can solve problems for other customers and improve their experiences. Artificial social skills should consist of four components: *influence*, *rapport, judgment, and collaboration*. Influence is the capacity of an artificial social skills algorithm to engage customers to share their experiences and spread positive word-of-mouth reviews and recommendations, both online and offline. Rapport is the capacity of an artificial social skills algorithm to connect continuously and emotionally with customers over the long term, during and outside the purchase process. It is all about creating genuine emotional connectedness and empathic concern with customers to sustain outcomes of interactivity such as positive relationships, positive reputation, and a high level of trust. Judgment is the capacity of an artificial social skills algorithm to make prosocial and ethical decisions with customers. Finally, collaboration is the capacity of an artificial social skills algorithm to encourage creativity and innovation with engaged customers. A social robot or a conversational agent powered with an artificial social skills algorithm could increase value co-creation with customers at the stage of advocacy of the automated customer journey. For instance, a social robot or a conversational agent powered with an artificial social skills algorithm could engage customers with gamification to create delightful experiences to speed up the advocacy process.

Table 12 summarizes the five components of EAI.

Table 12: Summary of Emotional Artificial Intelligence Components and Sub-components

EAI COMPONENTS	**EAI SUB-COMPONENTS**	**EAI AGGREGATIONS**
Artificial Awareness	*Detection, Adaptation*	Personal EAI
Artificial Regulation	*Reflection, Acceptance, Integrity*	
Artificial Motivation	*Perception, Cognition, Action*	
Artificial Empathy	*Contagion, Connection, Compassion*	Social EAI
Artificial Social Skills	*Influence, Rapport, Judgment, Collaboration*	

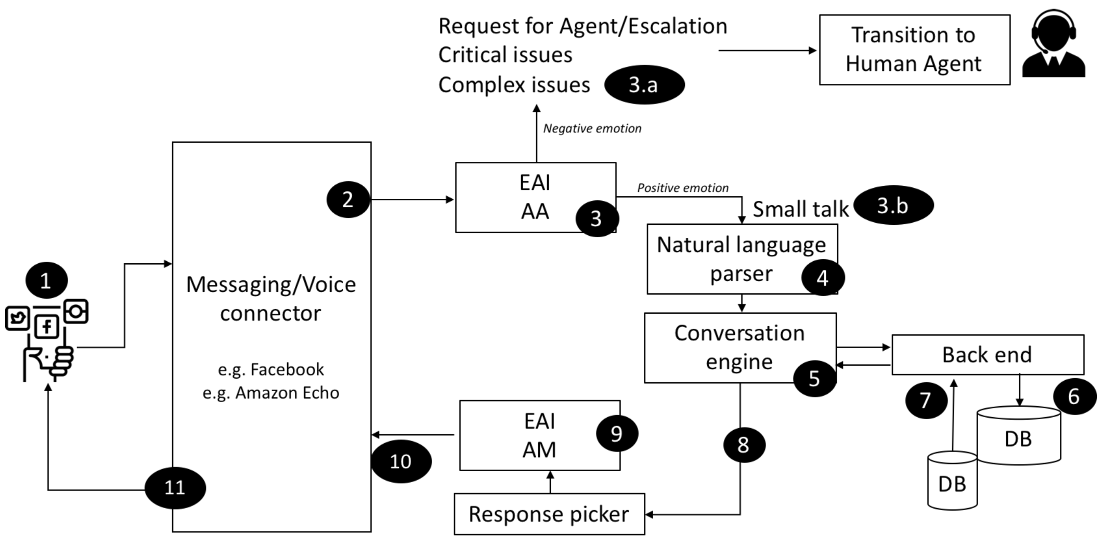
Nowadays, artificial regulation, artificial empathy and artificial social skills are components that are difficult to implement and surely will be interesting topics for future research; they represent the last stage of human intelligence that a robot or a conversational agent will be able to simulate or to master (Huang and Rust, 2018). The current chatbots are not powerful enough to encompass these emotional competences. However, artificial awareness and artificial motivation could be easily implemented in current AI-powered chatbots. In the following section, the chapter explores how both the artificial awareness and the artificial motivation components could leverage chatbots to identify the critical point when customers' negative emotions require the switch from the automated (chatbots) to a traditional, empathic (human operator) interaction.

Accordingly, firms would be able to manage all the required emotional competences for emotional connectedness and map the emotional customer journey thanks to an interaction between the two artificial components of the EAI model (artificial awareness and artificial motivation) and human competences related to EI (self-regulation, empathy, and social skills) of FLEs.

3.3 Emotional Artificial Intelligence-Powered Chatbots: A New Provisioning for Automated Customer Service

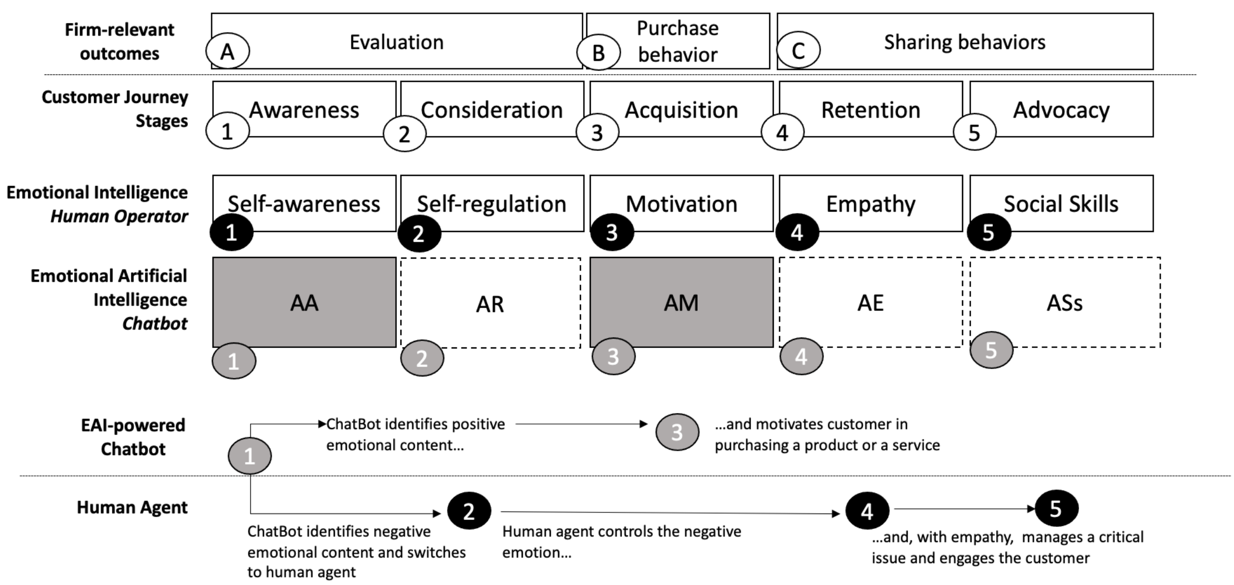
This paragraph introduces a new provision for automated customer service, where both the artificial awareness (AA) and the artificial motivation (AM) components of EAI upgrade the current technical process (Dempt, 2016) of a chatbot (Figure 9).

Figure 9: Technical Process of EAI-Powered Chatbots (adapted from Lajante and Del Prete, 2020)



When a customer activates a request on a product or service (steps 1 and 2), the EAI-powered chatbot captures the emotional content through an *artificial awareness* (AA) algorithm and identifies whether it is positive, neutral, or negative (step 3). If the emotion is neutral or positive (step 3.b), the EAI-powered chatbot activates its regular flow to generate a response picker (similar to Figure 6: steps 4, 5, 6, 7, 8). Before translating the answer into the natural language of the customer, the EAI-powered chatbot activates its artificial motivation (AM) algorithm to transform the initial positive emotion into a purchase behavior by motivating and engaging the customer (step 9). When the EAI-powered chatbot identifying negative emotional content during a conversation with a customer (thanks to its artificial awareness (AA) algorithm; step 3.a), it sorts this customer experience as a critical issue and switches the request to a human operator. Afterward, a human operator can manage the customer's negative emotion by connecting emotionally with the customer (i.e., regulation competence of EI)[17] and showing empathy (i.e., empathy and social skills competencies of EI), which enables it to develop prosocial responses to the customer's concerns and need for assistance (Figure 10).

Figure 10: Emotional Artificial Intelligence in Firm-Customer Interactivity



---

[17] See Chapter 2, Paragraph 2.3.

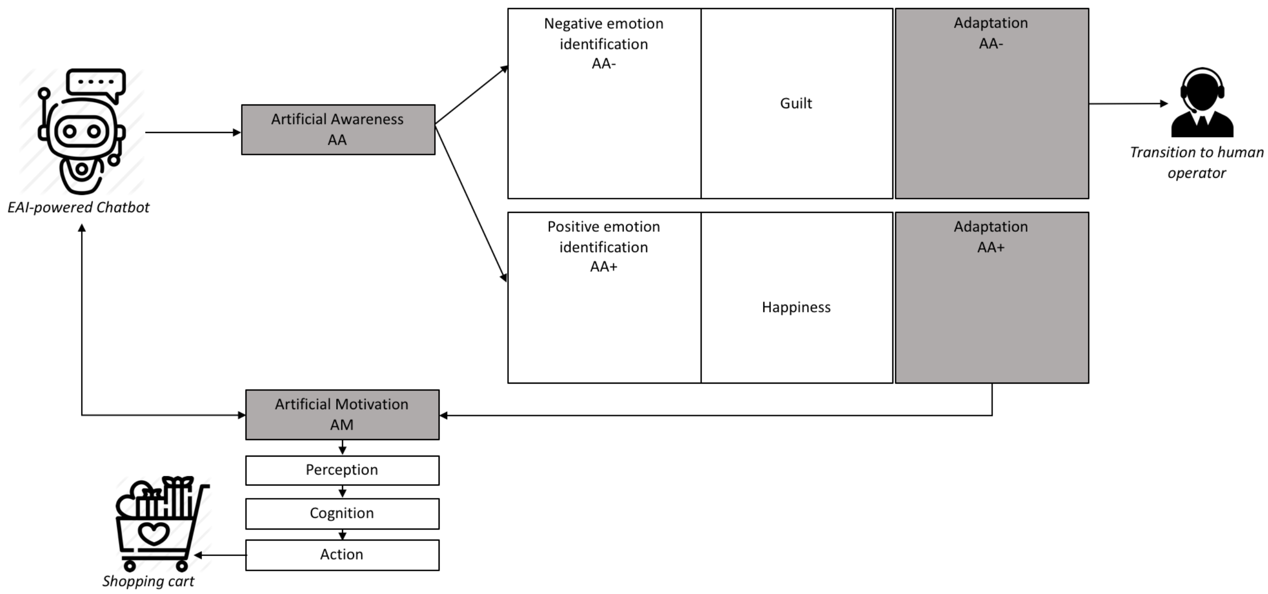
3.4 Emotional Artificial Awareness (AA) and Emotional Artificial Motivation (AM) Algorithms

An artificial awareness algorithm of an EAI-powered chatbot could provide valuable assistance in managing customers' emotions at the frontline, especially for differentiating positive from negative emotions and for sorting these emotional conversations into positive and negative categories for further analysis and decision-making. This automation of customers' emotion management could protect FLEs from emotional distress and empathic fatigue. Emotional labor[18] associated with repeated interactions with customers in service ecosystems can be exhausting. Putting the emphasis exclusively on the affective component of empathy, sharing customers' affective states, as well as on emotionally identifying with customers (self-other confusion) is likely to elicit emotional distress and burnout rather than prosocial responses in FLEs (Miller et al., 1995). From a clinical psychology perspective, focusing only on the emotional dimension at the expense of the cognitive one unbalances the FLEs' empathic capacity that would lead to asocial or even antisocial behaviors (Zaki and Ochsner, 2016).

When EAI-powered chatbots identify positive emotional content in a conversation (the customer is chatty, happy, surprised, or grateful) no human operator is required (*Adaptation AA+*; Figure 11). Both the artificial awareness and artificial motivation components of EAI-powered chatbots could have an impactful and relationship-enhancing conversation with customers by learning how to engage customers in multiple automated interactions, and how to transform the positive emotional state into motivation and purchasing behavior (Figure 11). Accordingly, EAI-powered chatbots need to switch their business tone to a friendly and affective one.

[18] See Chapter 1, Paragraph 1.3.5.

Figure 11: Role of Artificial Awareness and Artificial Motivation Components of EAI-Powered Chatbots



Note: Figure adapted from Lajante and Del Prete (2020).

When EAI-powered chatbots identify negative emotional content in a conversation (the customer is angry, anxious, frustrated or disappointed) a human operator is required (*Adaptation AA-*; Figure 11). This refers to the switch point in the automated customer journey (Lajante and Del Prete, 2020). Indeed, the EAI-powered chatbots rely only on the artificial awareness and the artificial motivation components of the model to identify customers' emotions and make a decision for the ongoing interaction. When negative emotional content appears in a conversation with a customer, the EAI-powered chatbots cannot rely on the self-regulation, empathy, or social skills competences to manage critical issues. Technical characteristics and specific features of EAI-powered chatbots do not allow them to activate an empathic connection with customers: this is the capacity of FLEs.

Empathy is a human developmental trait, but it is also FLEs' expected professional capacity for successful service delivery (Parasuraman et al.,1985; Zeithaml et al.,1996). As FLEs represent the firm to customers, they must align their behavior with the firm's positioning (Sirianni et al., 2013) and respond to customers' queries in a prosocial way (Brief and Motowidlo, 1986). They must display empathic listening (Aggarwal et al., 2005), recognition of customers' unique needs (Wilder et al., 2014), personal service and/or advice (Coulter and Ligas, 2004), and friendship (Bitner 1995). During this emotional interaction with customers, the dyadic service encounter (rather than the automated service encounter such as a chatbot) is the focal point in customers' evaluation of the entire firm through its capacity to connect emotionally with them by means of empathic interactions. Here, it refers to the firms' empathic capacity (Lajante, 2019): a voluntary organizational policy intended to develop, maintain, and monitor the ability to share as well as to decode, in perfect balance, the customers' affective and mental states in order to engage customers in prosocial, collaborative, and co-creative relationships. This sociobiological capacity of FLEs features two independent, but interacting components: the affective component, mainly automatic and unconscious (*experience sharing*); and the cognitive component, more controlled and cognitively mediated (*decoding*). Both components are jointly required for eliciting a genuine empathic response: the prosocial action tendency. For instance, FLEs adapt their behaviors by altering various interpersonal communication elements (variations in the level of vocabulary used in the service encounter, personality style, delivery speed, tone of voice, gestures, facial expressions, and encounter control) to meet what they perceive to be the unique needs of an individual customer (Bettencourt and Gwinner, 1996). This personalization of service delivery is necessary when customers need assistance and seek human interaction: it is the key element for developing successful relationships. Socialization between firms and customers enables stronger emotional connectedness and engagement over the long run (Coulter and Ligas, 2004). Whatever the medium used to respond to customers' negative emotion (face-to-face, phone, social media), a physical, human presence is always required. In order to avoid any emotional exhaustion when repeatedly dealing only with angry or anxious customers, FLEs must master the socio-affective route as well as the socio-cognitive route of empathic capacity. Accordingly, carefully recruiting and training FLEs is mandatory to elicit genuine empathy that would be reflected in the interactions promoting emotional connectedness and prosociality along the customer journey.

After a careful analysis of the literature on the discrete emotions that emerge during service encounters[19], this work focuses its attention on two specific emotions, one positive and the other negative (happiness and guilt). In the fourth chapter a cross-sectional research design through a self-administered questionnaire, preparatory to the validation of our EAI-powered chatbots framework has the aim to evaluate the significance of emotional awareness for the customer acceptance of chatbots with respect to these two emotions. The effects of these two emotions both during the interaction with a human operator and during the exchange with a conversational agent (chatbot) are surely different. It is also necessary to evaluate the chatbot's current ability to recognize and map these customer emotional states and respond appropriately to manage them.

3.5 Final Remarks

The main goal of this chapter was to introduce the EAI framework to sustain customer engagement throughout the automated customer journey. We discuss the utility of AA and AM components for EAI-powered chatbots in order to manage customers' negative emotion and, over the long term, to sustain emotional connectedness, empathic capacity, and customer engagement thanks to a collaboration with FLEs.

This study has identified several important implications for service managers. EAI is a new concept that supports firm-customer interactivity and promotes collaboration and value co-creation by preserving emotional connectedness and customer engagement in automated customer service. The EAI-powered chatbot is a concrete application where emotion-related sociobiological processes are pushed forward for the sake of customer satisfaction. In particular, this chapter defines in an exhaustive manner the five components of EAI identifying as *personal EAI:* artificial awareness, artificial regulation, artificial motivation; and as *social EAI:* artificial empathy, artificial social skills. The framework introduced in this chapter assumes that an EAI-powered chatbot could use only the two components of AA and AM, which entails a need for supporting intelligent systems throughout

[19] See Chapter 1, Paragraph 1.2.1.

the automated customer journey by means of human operators and dyadic, physical interaction. This point echoes several studies that recently highlighted the imperative need to develop and manage engagement ecosystems based on both physical and digital encounters (Blut et al., 2016; Breidbach et al., 2014; Huang and Rust, 2018; Larivière et al., 2017; Lemon and Verhoef, 2016; Oström et al., 2015). Accordingly, EAI-powered chatbots endowed with AA and AM algorithms, and FLEs trained for self-regulation, empathy, and social skills can collaborate to connect emotionally, empathize with and engage customers.

For the remaining components of the EAI, we suggest carrying out more studies and research. Future studies, for example, can explore the possibilities for service robots to utilize all the components of EAI to feel customers' emotions, connect emotionally with them, and influence their behavior.

CHAPTER 4. UNDERSTANDING CUSTOMER ACCEPTANCE OF AI TECHNOLOGIES IN SERVICE ENCOUNTERS: DRIVERS AND MODERATORS OF CHATBOTS ADOPTION

4.1 Introduction

In order to be able to enrich the study of the EAI framework and to define exactly the switch point (Lajante and Del Prete, 2020) between a chatbot and a human operator (in order to manage complex issues without losing customer engagement), we investigated the customer acceptance of the chatbots according to the sRAM model of Wirtz et al. (2018)[20] with a specific focus on its potential moderators. In particular, this chapter intends first to define the research framework and the hypotheses relating to the assessment of customer acceptance of chatbots. It will analyze what we argue may be potential moderators (1) technology literacy and 2) emotional awareness with a specific focus on the two emotions of *guilt* and *happiness,* for the reasons that emerged from the literature review in Chapter 1.

Chapter 4 continues with the definition of the methodology and the administration of the self-administered questionnaire. After the data collection and data analysis of the chosen samples, it defines the main results with discussions and final remarks.

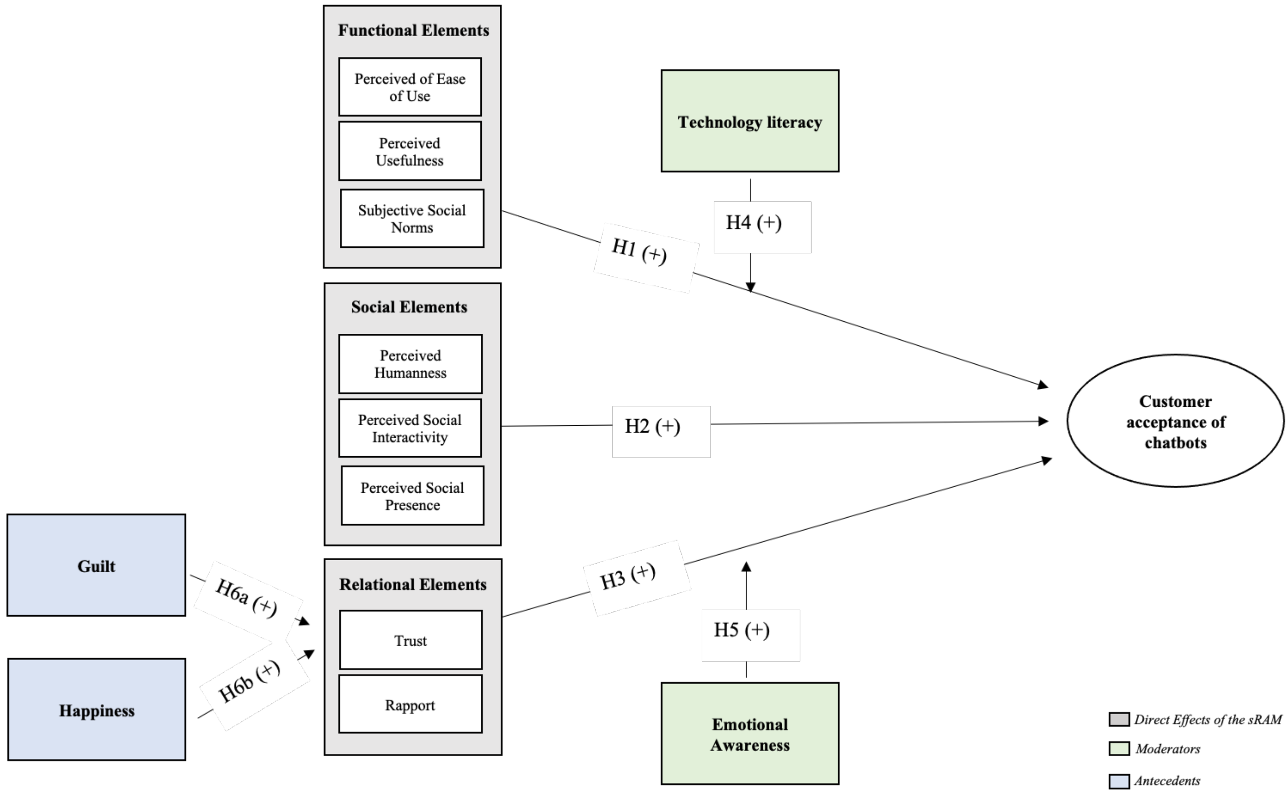
4.2 Research Framework and Hypotheses Development

According to the sRAM model of Wirtz et al. (2018), customer acceptance of chatbots depends on the functional, socio-emotional, and relational answers that chatbots are able to give to satisfy their needs (Davis, 1989; Solomon et al., 1985; Fiske et al., 2007). Wirtz et al. (2018) define service robots as "system-based autonomous and adaptable interfaces that interact, communicate and deliver service to an organization's customers" (p.909) that have physical (Chattaraman et al., 2019) but also virtual representations (e.g.DVA). As we have seen in Chapter 2, the sRAM (Wirtz et al., 2018) builds on the original TAM by adding social-emotional and relational variables as determinants of service robots' acceptance. The theoretical basis of the sRAM are Role Theory (Solomon et al., 1985) and the Stereotype Content Model (SCM) by Fiske et al. (2007). Role Theory defines that functional, social, and cultural norms dictate how service providers/robots and customers must act in a particular

[20] See Chapter 2, Paragraph 2.5.1, Figure 7.

situation. The SCM is based on the two dimensions of perceived warmth and competence. The *warmth* dimension refers to perceived intentions, such as friendliness, while the *competence* dimension relates to perceived abilities, such as intelligence (Fiske et al., 2007). According to the SCM, both the warmth and competence dimensions can be applied in service robots. As such, in this case, customer acceptance will depend on how well robots can deliver on the functional needs (related to competence) and the social-emotional and relational needs (related to warmth). Based on the sRAM (Wirtz et al., 2018), Figure 12 defines our research framework.

Figure 12: Research Framework Adapted from Wirtz et al. (2018)



Direct effects of the sRAM (Wirtz et. al, 2018)

Functional elements (TAM Model)

Functional elements (Figure 12) represent the core of the sRAM. *Perceived ease-of-use*, such as described in Chapter 2, is the simplicity with which the customer believes he can use the chatbot, while *perceived usefulness* corresponds to the perceived advantage of the customer in using the chatbot rather than other channels. Both dimensions are expected to have a direct and positive impact on the acceptance of automated service technologies such as conversational agents. According to Venkatesh and Davis (2000), subjective social norms are related to people's beliefs about what important referents think they should (or shouldn't) do about a certain situation. These norms may have a positive impact on the customers' acceptance of the chatbots, as people often act in relation to the opinion of society and referents (Schepers and Wetzels, 2007). The fact that new AI technologies are becoming trendy and socially recognized makes the customer motivated to use them for a sense of belonging to peer groups and for his social status (McLean and Osei-Frimpong, 2019).

For these reasons we expect that:

H1: Functional elements of the sRAM (perceived usefulness, perceived ease-of-use and subjective social norms) have a positive influence on customer acceptance of chatbots.

Social elements

Perceived humanness, social interactivity and social presence are the social elements of the sRAM. Perceived humanness represents the anthropomorphic qualities of a service robot (Wirtz et al., 2018). Customers tend to anthropomorphize technology (Epley et al., 2008) and when it happens, they experience feelings of connection towards the non-human agent (van Pinxteren et al., 2019). Mende and colleagues (2019) and some authors such as Duffy (2003) believe that this ability has more disadvantages than advantages.

For example, Duffy (2003) argues that a robot should not be a synthetic human because the greater the automorphism displayed, the greater the customers' expectations of the capabilities of service robots. Mori's (1970) "Uncanny Valley" theory argues that the more the robot resembles a human, the greater the sense of familiarity, a phenomenon known as the Eliza Effect (Kim et al., 2019); but since a robot is unable to be 100% human this can lead to a total disruption of the acceptance of service robots (Tinwell et al., 2011; van Doorn et al., 2017).

If the chatbot displays "emotions" according to social norms, it has a perceived social interactivity (Wirtz et al., 2018). According to Chattaraman et al. (2019), customers feel they can interact with artificial agents as they do with other humans in response to voice messages, conversations, or other elements that resemble human-like behavior. Greater interaction with technology could be justified by the fact that the artificial agent displays social skills and assists its users with pleasure (McLean and Osei-Frimpong, 2019).

Thanks to the social presence the artificial agent makes individuals feel as if they are in the presence of another social entity (Heerink et al., 2010). While interacting with the chatbot, the customer may believe that it is really "present" (Wirtz et al., 2018), which can affect how it is perceived and accepted (Belanche et al., 2019). For these reasons we, therefore, expect that:

H2: Social elements of the sRAM (perceived humanness, perceived social interactivity, perceived social presence) have a positive influence on customer acceptance of chatbots.

Relational Elements

Relational elements included in the sRAM by Wirtz et al. (2018) are *trust* and *rapport*.

Trust represents the security felt by users that the artificial agent is reliable, especially in the management of personal data (Chattaraman et al., 2019). Trust represents the customers' confidence in a service robot (Wirtz et al., 2018).

Rapport is the customer's perception that the chatbot is caring and sympathetic and that a personal connection between the customer and the chatbot exists (Wirtz et al., 2018). The presence of rapport is therefore quite important, especially in personal care services, where social closeness and affiliation are central to a service.

For these reasons we expect that:

H3: Relational elements of the sRAM (trust and rapport) have a positive influence on customer acceptance of chatbots.

Moderators

According to Chi et al. (2020), potential moderators of the relationship between AI agents and customer acceptance require further exploration. Belanche et al. (2019) call for more research into the role played by personal factors in human-robot service encounters. We argue that technology literacy, emotional awareness (the capacity to detect positive, neutral, and negative emotions), and the need for human interaction in particular –along with specific emotions such as guilt (Kranzbühler et al., 2020) – are among the most important moderators to consider. The extended TAM and UTAUT models (Venkatesh and Bala, 2008; Venkatesh et al., 2003, 2012)[21], suggest a number of moderators, including technology literacy and the need for human interaction (Blut et al., 2016; Dwivedi et al., 2019).

Technology Literacy

Technology experienced customers are able to consider artificial agents as easy to use, interactive, efficient, reliable, and enjoyable, while less technologically savvy customers may consider chatbots as stressful and feel less confident interacting with them (Fernandes and Pedroso, 2017).

Previous experience in new technologies plays an important role in the adoption of chatbots. The opposite is true for digitally infrequent users, who face several online barriers and are likely to experience feelings of alienation and anxiety when interacting with a chatbot (Chattaraman et al., 2019).

For these reasons we expect that:

H4: The relationship between functional elements and customer acceptance of chatbots is moderated by technology literacy.

[21] See Chapter 2, Paragraph 2.5.1.

Emotional Awareness

Having an awareness of customer emotions, in order to fully satisfy their needs during a service interaction, has positive effects on customers' intentions to return and recommend the service to others (Grandey, 2003). As we have seen previously, FLEs' emotional awareness is able to manage complex issues and establish an emotional connectedness with customers as the basis of a solid intimate and empathic relationship (Pansari and Kumar, 2017). In the third chapter of this thesis, we argued that a chatbot endowed with emotional awareness is able to understand the switch point at which a complex issue must be diverted to a human operator so that this empathic relationship with the customer can continue (Lajante and Del Prete, 2020). We thus expect that emotional awareness has a moderating effect on the acceptance of chatbots.

In particular, we posit that:

H5: The relationship between relational elements and customer acceptance of chatbots is moderated by emotional awareness.

Antecedents

Positive and Negative Emotion on Relational Elements of the sRAM (Wirtz et al., 2018)

Having defined in the first chapter the two emotions (one negative and the other positive) that are most relevant during firm-customer encounters (i.e., guilt and happiness), we argue that a correct chatbot recognition of these two emotions could enhance relational elements of customer acceptance of chatbots. The emotion of guilt, in fact, is the one that most often requires an exclusive interaction with the human operator in order to have a moderating effect on the emotion (Kranzbühler et al., 2020). Guilt is considered to be an adaptive emotion because it motivates positive changes and when people experience guilt, they will try to mend the situation by apologizing or engaging in other reparative actions (Tangney and Dearing, 2002). When customers experienced guilt for not making a purchase after interacting with a service employee, they indicate that they are likely to engage in reparative actions during future interaction in the form of making a purchase (Dahl et al., 2005). We argue that the chatbot's recognition of guilt and the consequent diversion of the call to the human operator as foreseen by our EAI framework[22] impacts chatbots acceptance thanks to a positive influence on trust and rapport elements of the sRAM of Wirtz et al. (2018), activating a customer repatronage intention.

We thus expect that:

H6a: Guilt has a positive influence on the relational elements of the sRAM of Wirtz et al. (2018).

Happiness, on the other hand, is able to impact the three main firm-relevant outcomes (evaluation, purchasing and sharing behaviors) (Kranzbühler et al., 2020) and we argue that if recognized by the chatbot it can make the customer journey more enjoyable, improving the relational elements of rapport and trust in the sRAM (Wirtz et al., 2018).

For these reasons we posit that:

H6b: Happiness has a positive influence on the relational elements of the sRAM of Wirtz et al. (2018).

4.3 Methodology

Data collection

Data was collected via a crowdsourcing platform, followed by data preparation, cleaning, and filtering. Crowdsourcing platforms are satisfactory ways to provide a random pool of participants across which studies related to attitudes and behaviors can be conducted (Hulland and Miller, 2018). The platform employed in this study is Amazon's MTurk (Miller et al., 2017). According to Gosling and Mason (2015), the use of online participant recruitment practices is one of the most significant changes in the social and behavioral sciences in the last 20 years. Chandler and colleagues (2019) affirm that "online recruitment provides an affordable way to reach participants, making it possible to recruit samples that more closely reflect the diversity of the US population or to selectively recruit hard to reach samples of participants" (p. 2022). We chose MTurk because this Amazon platform has

[22] See Figure 11, Chapter 3, Paragraph 3.3

established a common marketplace in which researchers and research participants can find each other, a reputation system to eliminate bad actors (Peer et al., 2014), and a secure means of paying participants.

The sample

Using Amazon's MTurk, **301 US customers** belonging to the millennial generation (i.e., born between the mid-80s and the early 2000s) were recruited to answer a self-administered, cross-sectional survey programming on Survey Monkey (a Survey software company similar to Qualtrics with the aim of simplifying the programming and fielding of web surveys). The AI industry is giving special attention to millennials since they tend to be early adopters with a greater predisposition towards new technologies (Liébana-Cabanillas et al., 2014). Millennials represent a technology savvy group (Bilgihan, 2016), who are very sensitive to trends (Schepers and Wetzels, 2007). 60% of millennials say they have used chatbots and 70% of them say they had a positive experience (Forbes 2018). Millennials were thus considered a relevant cohort for this study since our goal was to target users who exhibit some degree (although variable) of chatbots acceptance.

Scale validation and measures

The study employed purposive and convenience sampling techniques to recruit respondents targeting only participants familiar with chatbots. At the start of the survey, we inserted an initial filter question able to select only customers who have used a chatbot at least once during a service interaction. The reliability and validity of the measurement scales were tested from the data related to customer acceptance and its potential moderators. To address the problem of participant inattentiveness in online research panels, we implemented a pre-study screener that tested participants' attentiveness and basic English comprehension. The screener consisted of four questions that each presented a target word and asked participants to name a synonym. Questions measuring demographics were taken from the ANES (ANES, Stanford University and the University of Michigan, 2016).

Specifically, we asked participants questions about their gender, age, level of education, and job role. Four attention checks were included in the survey. The survey has up to 26 questions. Beside the screener, the main study of the survey included 10 questions adapted from the literature, measured with a seven-point Likert scale, ranging from “totally disagree” to “totally agree”. In order to minimize respondents’ fatigue, five-item scales were used to measure the drivers of functional elements, six-item scales were used to measure the drivers of social elements and four-item scales were used to measure the drivers of relational elements. Customer acceptance of chatbots was measured with three final questions. To measure the general customer acceptance of chatbots, the last three questions are adapted from Venkatesh et al. (2012) and the item scales are adapted from Heerink et al. (2010), van Pinxteren et al. (2019), Gremler and Gwinner (2000), and Venkatesh and Davis (2000). For what we argue to be the potential moderators of the Wirtz model (2018), the two-item scales to measure the technology literacy are adapted from Fernandes and Pedroso (2017) and the three-item scales of emotional awareness are adapted from Skjuve and Brandzaeg (2019). To measure the emotion of guilt the two-item scales are adapted from Pounders et al. (2018) and for happiness from Bagdare and Jain (2013).

Table 13 resumes the measurement items in relations to the previous hypothesis.

Table 13: Hypothesis and Measurement Items

Measurement Items	**Likert Scale**
H1: Functional Elements	
H1a: Perceived Ease-of-Use	
1) I find the chatbot easy to use.	• Strongly Disagree • Disagree • Somewhat disagree • Neither Agree nor Disagree • Somewhat Agree

	• Agree • Strongly Agree
2) I think I can use the chatbot without any help.	• Strongly Disagree • Disagree • Somewhat disagree • Neither Agree nor Disagree • Somewhat Agree • Agree • Strongly Agree
H1b: Perceived Usefulness	
1) I think the chatbot can help me for almost all my needs.	• Strongly Disagree • Disagree • Somewhat disagree • Neither Agree nor Disagree • Somewhat Agree • Agree • Strongly Agree
H1c: Subjective Social Norms	
1) People who influence me think I should use chatbots.	• Strongly Disagree • Disagree • Somewhat disagree • Neither Agree nor Disagree • Somewhat Agree • Agree

2) People important to me think I should use chatbots.	• Strongly Agree • Strongly Disagree • Disagree • Somewhat disagree • Neither Agree nor Disagree • Somewhat Agree • Agree • Strongly Agree
H2: Social-Emotional Elements	
H2a: Perceived Humanness	
1) Sometimes the chatbot seems to have real feelings. 2) I can imagine the chatbot to be a person.	• Strongly Disagree • Disagree • Somewhat disagree • Neither Agree nor Disagree • Somewhat Agree • Agree • Strongly Agree • Strongly Disagree • Disagree • Somewhat disagree • Neither Agree nor Disagree • Somewhat Agree • Agree

	• Strongly Agree
H2b: Perceived Social Interactivity	
1) I find the chatbot pleasant to interact with.	• Strongly Disagree • Disagree • Somewhat disagree • Neither Agree nor Disagree • Somewhat Agree • Agree • Strongly Agree
2) I feel the chatbot understands me.	• Strongly Disagree • Disagree • Somewhat disagree • Neither Agree nor Disagree • Somewhat Agree • Agree • Strongly Agree
H2c: Perceived Social Presence	
1) When I interact with a chatbot, it feels like talking with a real person.	• Strongly Disagree • Disagree • Somewhat disagree • Neither Agree nor Disagree • Somewhat Agree • Agree • Strongly Agree

2) I often think the chatbot is a real person.	• Strongly Disagree • Disagree • Somewhat disagree • Neither Agree nor Disagree • Somewhat Agree • Agree • Strongly Agree
H3: Relational Elements	
H3a: Trust	
1) I feel I can rely on the chatbot for my needs.	• Strongly Disagree • Disagree • Somewhat disagree • Neither Agree nor Disagree • Somewhat Agree • Agree • Strongly Agree
2) I believe the chatbot provides accurate information.	• Strongly Disagree • Disagree • Somewhat disagree • Neither Agree nor Disagree • Somewhat Agree • Agree • Strongly Agree
H3b: Rapport	
1)The chatbot relates well to me.	• Strongly Disagree • Disagree

	• Somewhat disagree • Neither Agree nor Disagree • Somewhat Agree • Agree • Strongly Agree
2) I believe there is an emotional connection between the chatbot and me.	• Strongly Disagree • Disagree • Somewhat disagree • Neither Agree nor Disagree • Somewhat Agree • Agree • Strongly Agree
H4: Technology Literacy	
1)I believe that my knowledge of new technologies facilitates my use of the chatbot. 2) I think less experienced people might have difficulty using the chatbots.	• Strongly Disagree • Disagree • Somewhat disagree • Neither Agree nor Disagree • Somewhat Agree • Agree • Strongly Agree • Strongly Disagree • Disagree • Somewhat disagree • Neither Agree nor Disagree • Somewhat Agree

	• Agree • Strongly Agree
H5: Emotional Awareness	
1) The chatbot seemed to know how I was feeling. 2) The chatbot seemed to understand me. 3) The chatbot put itself in my shoes.	• Strongly Disagree • Disagree • Somewhat disagree • Neither Agree nor Disagree • Somewhat Agree • Agree • Strongly Agree • Strongly Disagree • Disagree • Somewhat disagree • Neither Agree nor Disagree • Somewhat Agree • Agree • Strongly Agree • Strongly Disagree • Disagree • Somewhat disagree • Neither Agree nor Disagree • Somewhat Agree • Agree • Strongly Agree

H6: Antecedents	
H6a: Guilt	
1) I think the chatbot is able to recognize my guilt when I am unable to make a purchase. 2) The chatbot diverted me to a human operator when it recognized my guilt.	• Strongly Disagree • Disagree • Somewhat disagree • Neither Agree nor Disagree • Somewhat Agree • Agree • Strongly Agree • Strongly Disagree • Disagree • Somewhat disagree • Neither Agree nor Disagree • Somewhat Agree • Agree • Strongly Agree
H6b: Happiness	
1) I think the chatbot recognizes my happiness 2) I think the chatbot is able to give me a pleasant experience and motivate me if it recognizes my happiness.	• Strongly Disagree • Disagree • Somewhat disagree • Neither Agree nor Disagree • Somewhat Agree • Agree • Strongly Agree • Strongly Disagree

	• Disagree • Somewhat disagree • Neither Agree nor Disagree • Somewhat Agree • Agree • Strongly Agree
Customer acceptance of the chatbot	
1) I will try to use the chatbot in the future. 2) I plan to use the chatbot in the future. 3) I intend to use the chatbot in the future.	• Strongly Disagree • Disagree • Somewhat disagree • Neither Agree nor Disagree • Somewhat Agree • Agree • Strongly Agree • Strongly Disagree • Disagree • Somewhat disagree • Neither Agree nor Disagree • Somewhat Agree • Agree • Strongly Agree • Strongly Disagree • Disagree • Somewhat disagree

	• Neither Agree nor Disagree • Somewhat Agree • Agree • Strongly Agree

The survey concluded with the demographic and technical data (browser etc.) of the respondents.

Data Analysis

An analysis of variance (ANOVA) using the SPSS IBM software was employed. ANOVA is a statistical procedure concerned with comparing the means of several samples. It can be thought of as an extension of the t-test for two independent samples to more than two groups. The purpose is to test for significant differences between class means, and this is achieved through the analysis of the variances.

ANOVA is the most commonly quoted advanced research method in the professional business and economic literature. This technique is very useful in revealing important information particularly in interpreting experimental outcomes and in determining the influence of some factors on other processing parameters. In this study, we apply the one-way ANOVA because the data are divided into groups according to only one factor. The main purpose of an ANOVA is to test if two or more groups differ from each other significantly in one or more characteristics. The results of the calculations are related to the p-value, since the *p*-value is less than the given significance level of 0.05 for our hypothesis, we have rejected the null hypothesis.

4.4 Findings

434 US customers started the survey from MTurk but 14% stopped at the filter question and declared that they had never used a chatbot. The remaining 86% had at least one experience with a chatbot. Of these, 10% stopped at the initial screener and did not arrive at the main study, while the remaining

90% completed the study. 10% did not consent to the use of the data, declaring that they were unsure of the statements made. In total, only **301 respondents** completed the survey and gave their consent to use the data.

Of the 301 respondents, 145 (48%) are female and 153 (51%) of them are male. The number of respondents is evenly balanced between the two genders. Respondents' age distribution follows an asymptotically normal distribution. Most of them are below 40 years old.

45% of respondents have a bachelor's degree, whereas 30% are high school graduates and 17% are master's degree holders. 45% of respondents use the chatbot to request technical assistance on a product or service, 34% to request information on a product or service, 18% to make a complaint about a product or service. The least number of respondents (3%) use the chatbot to purchase a product or service. Chatbots are used principally in retail (38%), banking (17%) and telecommunication (11%) sectors.

Hypothesis testing

Based on the data collected using the questionnaires from the 301 respondents, we tested the hypotheses of our research framework (see Figure 12).

To test all the hypotheses, we have considered different indexes and calculated the ANOVA regression, using customer acceptance of chatbots as the dependent variable. In particular, we have calculated: 1) a *Functional Elements Index* by combining the average of the perceptions of five-item scales defined to measure *perceived usefulness*, *perceived ease-of-use*, and *subjective social norms*; 2) a *Social Elements Index* by combining the average of the perceptions of six-item scales defined to measure *perceived humanness*, *perceived social interactivity*, and *perceived social presence*; 3) a *Relational Elements Index* calculated by combining the average of the perceptions of four-item scales defined to measure *trust* and *rapport*.

Regarding the potential moderators, we have defined: 4) a *Technology Literacy Index* by combining the average of the perceptions of two-item scales, 5) an *Emotional Awareness Index* by combining the average of the perceptions of three-item scales.

Regarding guilt and happiness, we have calculated 6a) a *Guilt Index* by combining the average of the perceptions of two-item scales and finally 6b) a *Happiness Index* by combining the average of the perceptions of two-item scales (Table 13).

A *Customer Acceptance Index* was calculated through the average of the perceptions of three item-scales: a) *I will try to use the chatbot in the future; b) I plan to use the chatbot in the future;* and *c) I intend to use the chatbot in the future.*

In summary, the indexes were created in relation to the main elements of our research framework (Table 14).

Table 14: Hypotheses Test

Hypotheses		
Direct Effects of the sRAM		
H1	*Functional Elements index → independent variable* *Customer Acceptance index→ dependent variable*	*H_O: Functional elements of the sRAM (perceived usefulness, perceived ease-of-use, and subjective social norms) don't have a positive influence on customer acceptance of chatbots.* *H_A: Functional elements of the sRAM (perceived usefulness, perceived ease-of-use, and subjective social norms) have a positive influence on customer acceptance of chatbots.*
H2	*Social Element index → independent variable* *Customer Acceptance index→ dependent variable*	*H_O: Social elements of the sRAM (perceived humanness, perceived social interactivity, and perceived social presence) don't have a positive influence on customer acceptance of chatbots.* *H_A: Social elements of the sRAM (perceived humanness, perceived social interactivity, and*

		perceived social presence) have a positive influence on customer acceptance of chatbots.
H3	*Relational Elements index → independent variable* *Customer Acceptance index→ dependent variable*	*Ho: Relational elements of the sRAM (trust and rapport) don't have a positive influence on customer acceptance of chatbots.* *HA: Relational elements of the sRAM (trust and rapport) have a positive influence on customer acceptance of chatbots.*
Moderator effects of the sRAM		
H4	*Technology Literacy index → independent variable* *Customer Acceptance index→ dependent variable*	*Ho: The relationship between functional elements and customer acceptance of chatbots is not moderated by technology literacy.* *HA: The relationship between functional elements and customer acceptance of chatbots is moderated by technology literacy.*
H5	*Emotional Awareness index → independent variable* *Customer Acceptance index → dependent variable*	*Ho: The relationship between relational elements and customer acceptance of chatbots is not moderated by emotional awareness.* *HA: The relationship between relational elements and customer acceptance of chatbots is moderated by emotional awareness.*
Positive and Negative Emotions vs Relational Elements of the sRAM		
H6a H6b	*Guilt index → independent variable* *Relational Elements index→ dependent variable* *Happiness index → independent variable* *Relational element index → dependent variable*	*Ho: Guilt doesn't have a positive influence on the relational elements of the sRAM of Wirtz et al. (2018).* *HA: Guilt has a positive influence on the relational elements of the sRAM of Wirtz et al. (2018).* *Ho: Happiness doesn't have a positive influence on the relational elements of the sRAM of Wirtz et al. (2018).*

		H_A: Happiness has a positive influence on the relational elements of the sRAM of Wirtz et al. (2018).

Measures demonstrate good scale reliability according to accepted standards (Nunnaly, 1978). All variables measuring the same construct were statistically significant (p-value<.05) supporting convergent validity. To reduce potential common method variance, we used existing scales and ensured respondents anonymity (Podsakoff et al., 2012).

Having established the soundness of the indexes, we use them below to test the research hypotheses both for direct and moderator effects of the sRAM (Wirtz et al., 2018).

Direct effects

Regarding direct effects, we find a positive relationship between the **functional elements** (**H1**) and customer acceptance of chatbots, a 5% level of significance. We can confirm that the *perceived of ease of use*, *perceived usefulness*, and *subjective social norms* of functional elements of the sRAM (Wirtz et al., 2018) have a positive influence (p-value <.05) on chatbots acceptance. We also find support for **H2** with a positive relationship between **social elements** and customer acceptance of chatbots. We can confirm that *perceived humanness*, *perceived social interactivity*, and *perceived social presence* of the sRAM (Wirtz et al., 2018) have a positive influence (p-value <.05) on chatbots' acceptance. Regarding **H3,** we find that the **relational elements** of *trust* and *rapport* have a positive influence on customer acceptance, a 5% of significance (Table 15).

Table 15: Overview of the Direct Effects of the sRAM on Chatbots' Acceptance

Overview of direct effects	Direct effects of the sRAM		Chatbots Acceptance	p value
H1	Functional Elements	→	Customer Acceptance of chatbots	.000
H2	Social Elements	→	Customer Acceptance of chatbots	.000
H3	Relational Elements	→	Customer Acceptance of chatbots	.000

Note: Significant (p-value <.05)

Following these significant results, we have compared all direct effects and we find that only *functional elements* and *relational elements* have a positive influence (p-value <.05) on chatbots' acceptance while *social elements* don't have a significant influence when compared with the other two (Table 16).

Table 16: Comparison between the Direct Effects of the sRAM on Chatbots' Acceptance

Comparison between direct effects on chatbots acceptance	Direct effects of the sRAM		Chatbots Acceptance	p value
	Functional Elements			.000
	Social Elements			.487*
	Relational Elements	→	Customer Acceptance of chatbots	.000

Notes:
(i) Significant (p-value<.05)
(ii) *Non significant (p-value>.05)

Moderators

Regarding moderator effects, we find support for **H4** and **H5**. Both **technology literacy** and **emotional awareness** have a positive influence on chatbots acceptance. We tested the moderating effect of technology literacy on functional elements of the sRAM (Wirtz et al., 2018) and we found a positive influence (p-value<.05) among customers experienced in new technologies and the perception they have regarding *ease of use*, *usefulness*, and *subjective social norms* of chatbots.

We can confirm that the relationship between functional elements and chatbots acceptance is moderated by technology literacy (**H4**, Table 17).

Regarding the moderating effect of emotional awareness on relational elements of the sRAM (Wirtz et al., 2018), we found a positive influence (p-value<.05) on *trust* and *rapport* elements.

We can confirm that the relationship between relational elements and chatbots acceptance is moderated by emotional awareness (**H5**, Table 17).

Table 17: Overview of moderator effects

Overview of moderator effects	Moderators		Drivers	p value
H4	Tecnology Literacy	→	Customer Acceptance of chatbots	.000
H4	Tecnology Literacy	→	Functional Elements	.023
H5	Emotional Awareness	→	Customer Acceptance of chatbots	.000
H5	Emotional Awareness	→	Relational Elements	.000

Note: Significant (p-value<.05)

We have also observed the comparison between direct effects of the sRAM with the moderator effect of **technology literacy** and none of the *functional*, *social*, and *relational elements* have a positive influence on technology literacy, a 5% level of significance (Table 18).

Finally, a comparison between direct effects and **emotional awareness** was performed and we found that *social elements* and *relational elements* have a positive influence on emotional awareness, a 5% level of significance while *functional elements* are insignificant (p-value>.05) (Table 18).

Table 18: Comparison between the Direct Effects of the sRAM on Moderators

Comparison between direct effects on moderators	Direct effects of the sRAM		Moderators	p value
	Functional Elements			.464*
	Social Elements			.263*
	Relational Elements	→	Technology Literacy	.088*
	Functional Elements			.842*
	Social Elements			.000
	Relational Elements	→	Emotional Awareness	.000

Notes:
(i) Significant (p-value<.05)
(ii) *Non significant (p-value>.05)

Antecedents

We find also support for **H6a** and **H6b,** both *guilt* and *happiness* have a positive influence (p-value<.05) on *relational elements* of the sRAM (Wirtz et al., 2018).

We can confirm that the positive effect of guilt has a significant impact on *rapport* and *trust* elements for customers' repatronage intention. We also found that the recognition of the positive emotion of happiness has a significant impact on relational elements of the sRAM of Wirtz et al. (2018), making the customer experience more enjoyable (Table 19).

Table 19: Negative and Positive emotion on relational elements of the sRAM (Wirtz et al., 2018)

Antecedents	Negative or Positive Emotion		Drivers	p value
H6a	Guilt	→	Relational Elements	.000
H6b	Happiness	→	Relational Elements	.000

Note: Significant (p-value<.05)

4.5 Discussion

Although the service sector is making important developments thanks to the adoption of AI, the research is still in its infancy and has been mainly conceptual.

Therefore, based on data collected from 301 US millennials, this study focuses on drivers of chatbots adoption, drawing on the conceptual Service Robot Acceptance Model (sRAM) of Wirtz et al. (2018), with the plug-in of two moderator effects: technology literacy and emotional awareness. Overall, the sRAM (Wirtz et al., 2018) has been empirically validated and displays high predictive power.

Regarding chatbots' acceptance individuals are mainly motivated by **functional elements (H1)**; the drivers of the *perceived usefulness of chatbots*, *perceived of ease of use*, and *subjective social norms,* according to Wirtz et al. (2018), help users to satisfy utilitarian needs that often do not require any kind of social interaction.

Respondents to our survey interacted with the chatbot mainly to request technical assistance, request information or make a complaint. We can define these as utilitarian-driven needs and chatbots are designed to achieve instrumental goals (Kim et al., 2019). The influence of functional elements of Wirtz's model (2018) is particularly strong for technology experienced users **(H4).** Research suggests that customers more experienced in the use of a certain technology know how to use it better (Blut et al., 2016; Dwivedi et al., 2019), even if the opposite is not true as our empirical analysis in Table 18 shows. Our data **(H1)** validates that the relationships between the functional elements and customer acceptance of chatbots are positive as *increased ease of use*, *increased usefulness*, and *increasing congruency with social norms* lead to greater customer acceptance (Schepers and Wetzels, 2007). In the original TAM[23], ease-of-use is strictly correlated to perceived usefulness rather than a direct determinant of technology (Davis, 1989). This effect is weaker for customers that prefer human interaction. According to Gelderman and colleagues (2011), for those who prefer interaction with a FLE, the fact that the chatbot is functional or easy to use is less significant than a chatbot that has a user-friendly language (Dabholkar et al., 2003). Equally important for the technological assessments

[23] See Chapter 2, Paragraph 2.3.1.

of customers who prefer interaction with a human operator are social norms because they can lack the internal motivation to use service technologies (Gelderman et al., 2011). Social norms, in fact, are connected with external motivations such as pressures from important referents who believe in chatbots usefulness and are able to change peoples' opinion about them (Blut et al., 2016).

The cognitive complexity of service delivery may help to explain the significance of functional drivers. If service delivery mainly aims to fulfil utilitarian needs, customers are expected to value speed and convenience, since there is little need for social interaction.

Social elements are also significant direct variables of customer acceptance of chatbots **(H2)**, namely through perceived social presence, which in turn is influenced by social interactivity. When we compared the direct effects of sRAM with each other (Wirtz et al., 2018), we noticed that only the functional and relational elements of the model were significant for chatbots acceptance while the social elements were not significant (Table 17). We argue that the result is related to *perceived humaneness* which often in chatbots has no significant effect (direct or indirect). Social elements, according to limited research, also impact technology adoption based on the physical and virtual characteristics of chatbots, which are different from past technologies (De Keyser et al., 2019). Chatbots can mimic human-like language-based communication skills, which evoke a sense of social presence. To strengthen this point of view, several studies indicate that customers tend to anthropomorphize technology (Epley et al., 2008) and have always wanted to talk to computers as if they were social entities (Heerink et al., 2010). Perceiving humanlike characteristics in non-human agents is the essence of anthropomorphism. These humanlike characteristics may include physical appearance (Guthrie, 1993), emotional states perceived to be uniquely human (Leyens et al., 2003), or inner mental states and motivations (Gray et al., 2007). Such anthropomorphic representations are important determinants of how a person behaves towards these agents (Epley et al., 2008).

According to Epley et al. (2007), two motivational factors are important determinants of anthropomorphism: sociality and effectance motivation. Sociality motivation is the fundamental need for social connection with human operators. When lacking social connection with FLE, people may compensate with non-human agents such as chatbots through anthropomorphism. Anthropomorphism satisfies effectance motivation by providing a sense of understanding and control of a chatbot and should therefore increase as effectance motivation increases. Customers who are particularly fond of feeling in control of one's environment, for instance, should be especially likely to anthropomorphize in times of uncertainty.

However, it is important to underline that only AI has allowed an increasing level of social presence for machines (Chattaraman et al., 2019) understood as *perceived interactivity*. Social interactivity is the extent to which individuals feel they can communicate synchronously and reciprocally with the conversational agent (Chattaraman et al., 2019) according to societal norms (Wirtz et al., 2018) as they do with other humans. In traditional service encounters, the ability to interact has been found to generate positive emotions and social bonds with customers, thus leading to increased levels of *trust* and *rapport* **(H3).** Similarly, if customers perceive chatbots as a quasi-*social presence*, trust and rapport can also exist (van Doorn et al., 2017; Qiu et al., 2020) **(H3)**, albeit differently from those established among humans (Gremler and Gwinner, 2000).

Relational elements (**trust** and **rapport)** have been identified as the second most important direct variables of customer acceptance of chatbots **(H3).**

Little research has investigated the weight of relational elements for the acceptance of chatbots.

For example, van Pinxteren et al. (2019) studied the impact of *trust* on customers' usage intention regarding humanoid forms but *rapport* effects remain virtually unexplored. This is why our research tried to understand how emotional awareness could impact *trust* and *rapport*. In this regard, we have verified that for the two specific emotions of *guilt* and *happiness*, recognition is absolutely significant for raising *trust* and creating a *rapport* in customer service. The emotional competence of chatbots can certainly raise the value of relational elements and their significance on customer acceptance. *Rapport* is a bond represented by the emotional connection created between a service employee and the customer (Gremler and Gwinner, 2000). In the first chapter, we saw how this relationship can mediate with respect to negative customer emotions and consequently change the service experience, in particular with adaptive negative emotions such as *guilt* **(H6a)**. Therefore, in an analysis that takes into account *emotional awareness* **(H5)**, as a moderating effect for the acceptance of chatbots, we cannot fail to attribute a significant weight to the *relational elements*; the significance of which is also justified by our empirical analysis. Specifically, relational elements were considered an important driver of the acceptance of chatbots **(H3)**, also for the segments of young customers. Millennials tend to emphasize emotional value in their interactions.

Regarding our two moderator effects **technology literacy (H4)** and **emotional awareness (H5)**, both have a strong significance for the acceptance of chatbots by respondents.

In particular, with regard to the experience in using new technologies, what has been demonstrated through the empirical analysis is that there is a strong significance between customers' *technology literacy* and the level of chatbots acceptance **(H4)**. We verified, in fact, that *technology literacy* has a positive influence on the functional elements of the sRAM (Wirtz et al., 2018). We argue that customers who are more inclined to use new technologies are more willing to use chatbots during service encounters **(H4).** Our analysis has brought out another significant aspect, given a certain technology with its own functional, relational, and social elements, these are not significant results for increasing customer technology literacy **(H4).**

Regarding **emotional awareness (H5)** is certainly a moderating effect of the customer acceptance of chatbots as the degree of significance in our analysis is very strong. We have shown that *emotional awareness* has a positive influence on **relational elements** of sRAM (Wirtz et al., 2018) **(H5)**.

We argue that the recognition of customer emotions generates an emotional connectedness[24] capable of generating a man-machine *rapport*. If the chatbot recognizes negative emotions, it is able to divert the call to a human operator as proposed in our EAI framework[25] and the significance that a chatbot knows how to detect emotions to make the customer experience more pleasant was also confirmed by our empirical analysis **(H5** and **H6).**

[24] See Chapter 1 and 2.
[25] See Chapter 3.

Our study also confirmed another very important aspect. When we compared all the direct effects of sRAM (Wirtz et al., 2018) in relation to **emotional awareness**, significance was present only for *social* and *relational elements* but not for *functional elements*. This implies that the fact that a chatbot is equipped with *social presence* and *perceived humanness* or is able to convey *trust* and *rapport* is absolutely significant for emotional recognition **(H5).** Our research findings demonstrate that customers are favorable to finding emotional awareness in chatbots. For them, this is an essential part of natural interaction. Hence, endowing chatbots with EI can help service managers ensure a more pleasant user experience. This complies with the Media Equation theory (Reaves and Nass, 1996), suggesting that people apply rules and conventions of social human interaction to computers. Our results confirm that customers appear considerably more positive about the chatbot and their interaction experience with it if a chatbot detects their emotional needs. Customers perceive such technology as friendlier and more supportive and feel more comfortable with it.

To enrich our study, we explored the chatbots' ability to detect two specific emotions, one with a negative valence (**Guilt**)[26], and the other with positive valence (**Happiness**).

In particular, we analyzed the significance of guilt and happiness on the relational elements of the sRAM (Wirtz et al., 2018).

Regarding the negative emotion of guilt **(H6a)**, this work focuses on how customer service handles *interpersonal reactive guilt* thanks to AI. In our investigation, we mainly focused on the level of significance of the acknowledgment of *customer-created guilt* (Tangney and Dearing, 2002) and the impact of this acknowledgment on the relational elements of the sRAM. The choice to verify the influence of guilt on the relational elements of the Wirtz et al. (2018) model depends on what emerged from the analysis of the literature regarding the moderating effect of the human operator for this emotion. In our empirical analysis, we have shown that the recognition of guilt has a significant impact on the relational elements of the sRAM **(H6a)** for customer repatronage intentions. Survey findings reveal that affective commitment fully mediates the relationship between guilt and

[26] As emerged from the literature review in Chapter 1, the effect of Guilt significantly differed between interaction involved or not involving FLE. Specifically, there is a positive significant average effect size for guilt for interaction with FLEs.

repatronage intention if trust and rapport (relational elements) in the customer perception are strong. In the case of guilt, *rapport* between customer and chatbot can only be strengthened if the chatbot, recognizing the negative emotion, diverts the request towards the human operators so that they can manage it. For this reason, we asked the participants if the chatbot, detecting guilt, was able to divert to a human operator or not. Respondents recognized an inability to acknowledge guilt on the part of the chatbot and highlighted this lack **(H6a).**

Regarding the positive emotion of happiness **(H6b)**, we asked the respondents if the chatbot, recognizing this emotion, was able to make the service experience more enjoyable and motivate the customer. We found that the recognition of the positive emotion of happiness has a positive influence on relational elements of the sRAM of Wirtz et al. (2018) making the customer experience more enjoyable. The chatbot's recognition of a customer's positive emotional state is certainly functional to his engagement. As proposed in Chapter 3, in our EAI framework, a chatbot that detects customers' happiness could motivate them to purchase or make the browsing experience more enjoyable.

Previous research demonstrates that happiness is often related to a shopping experience, especially in the retail sector (Jin and Sternquist, 2004). We argue that if a chatbot detects happiness, it can lead the customer into an engaging dimension based on active participation in the entire purchasing process (Gilmore, 1988). It has also been found that happiness is a source of motivation (Dennis, 2005) and therefore, as defined in our model, the chatbot, recognizing happiness, could be able to motivate the customer to purchase new products or services[27]. Failure to recognize positive emotion could result in avoidance behaviors during shopping (Patwardhan and Balasubramanian, 2011). Our empirical analysis has demonstrated the feasibility of this positive emotional bond because the recognition of happiness influences the relational elements of the sRAM (Wirtz et al., 2018; **H6b**).

4.6 Final Remarks

During this last chapter, the main research findings were presented and discussed. In preparation for the validation of our EAI framework, we carried out an empirical analysis on customer acceptance of

[27] See Chapter 3, Figure 15.

chatbots using the model of Wirtz and colleagues (2018). We chose this framework because unlike TAM (Davis, 1989) or UTAUT (Venkatesh and Davis 2000), the sRAM (Wirtz et. al., 2018) also considers social and relational elements as essential components of service robots' acceptance. These components are strongly linked to emotional awareness and to the role of emotions during service encounters as investigated in this thesis. For this reason, in the first instance, we validated the Wirtz model (2018) in its main direct drivers (functional elements, social elements, relational elements) through our empirical analysis. Subsequently, we considered technology literacy and emotional awareness as moderator effects of the sRAM, demonstrating that both have a positive influence on chatbots' acceptance. We also found that if technology literacy influences the functional elements of the sRAM of Wirtz and colleagues (2018), emotional awareness is able to positively affect the relational elements.

Finally, we tested the chatbots' ability to recognize two specific emotions: guilt and happiness (justified by the analysis of the literature carried out). We have shown through our investigation that the chatbot is currently unable to recognize these two emotions specifically but that these emotions are highly significant in strengthening the relational elements of the sRAM model.

Our findings set the groundwork for the validation of our EAI framework which enables a chatbot to divert the customer's request when it recognizes guilt (negative emotion). The empirical analysis shows that this recognition is absolutely significant for strengthening the elements of trust and rapport and establishing an emotional bond with the customer, while keeping his engagement unchanged. In the case of the recognition of happiness, we demonstrated the significance both on the relational elements and on the motivation to purchase products or services by further validating the EAI framework.

Like any scientific activity, this research is not exempt from limits, both theoretical and methodological, which constitute research for future work. In particular, new moderating effects on other dimensions of EI (i.e., empathy) could be tested to validate the sRAM model. Even an analysis of indirect effects in relation to these new emotional moderators could be conducted to individually test not only the aggregate drivers but each individual component of the sRAM (Wirtz et. al., 2018). Finally, combining the measurements of human and chatbots interactions with respect to particular emotions (such as anger) could lead the way in validating the components of the EAI Framework not yet explored such as empathy and emotion regulation.

CONCLUSION

Theoretical contributions.

The contributions of this thesis are manifold.

First, we contribute to the literature on automated service technologies with a focus on customer emotions during service encounters (Chapter 1 and 2), which is still in its infancy and has been largely conceptual (Lu et al., 2020). In particular, while the attention of academics to this new topic is growing, the literature still lacks a thorough understanding of the factors that drive chatbots acceptance and, in particular, there is little research on emotions and EI as moderator effects. Research on chatbots acceptance and emotions is scarce and fragmented. Additionally, current customer-centred empirical studies often replicate established adoption frameworks (e.g., TAM, UTAUT) which can be limiting, as the effectiveness of these theories largely depends on context. Furthermore, these frameworks predominantly focus on functional attributes, without fully encapsulating the expanded dimensionality of emotional aspects of automated technologies (Lin et al., 2019). While adopting a context-specific framework that explores not only utilitarian but also emotional, social, and relational drivers, we contribute to a more holistic understanding of chatbots acceptance.

Second, responding to Kranzebhuler and colleagues' (2020) call for more research on drawing an emotional customer journey map, we designed the EAI framework, which combines firm-relevant outcomes, customer journey, EI, and AI (Chapter 3). Through EAI we defined a new provision for automated customer service capable of making an emotional reading of the customer experience. On the basis of the literature review, we defined the main components of our EAI framework (i.e., artificial awareness (AA), artificial regulation (AR), artificial motivation (AM), artificial empathy (AE), and artificial social skills (ASs)) but we argued that only the components of artificial awareness and artificial motivation could easily be implemented with current theoretical knowledge on chatbots. In our opinion, chatbots cannot completely replace human operators but there must be collaboration. This collaboration is justified if the chatbot is able to detect customer emotions and when complex issues occur, divert the call to a human operator. The contribution of the EAI framework to research is linked to value co-creation in automated service interactions. In fact, we know from previous research, that interaction with a service robot such as chatbots can co-create but also co-destroy value (Čaić et al., 2018). We argued that this happens because the chatbot is unable to satisfy customers' emotional needs. By detecting feelings, emotions, and moods, the chatbot could have an emotional recognition skill to establish the exact switch point (Lajante and Del Prete, 2020) at which a complex issue needs to be transferred to a human operator. The EAI model is certainly the first attempt to approach the topic of automated service interactions from the point of view of customers emotions.

Third, thanks to the empirical research implemented in Chapter 4, we are the first to empirically validate the sRAM (Wirtz et al., 2018) in relation to chatbots. We built our analysis on previous conceptual research and refer to specific calls for more research with respect to customer preferences in relation to conversational agents (De Keyser et al., 2019). The fact that we considered a specific target (that of millennials) is to our advantage because the previous research is not very generational. The results show that although social elements are significant for customer acceptance of chatbots, when compared to functional and relational elements, they are still not able to fully deploy their power of action. This finding contributes to research on the uncanny valley phenomenon that occurs when robots seem too humanlike. The results also contribute to the research on service robots by adding a new relational perspective based on building the customer-chatbot *rapport* through the emotional reading of the customer experience, which was practically absent from previous empirical studies. Our study also contributes to research on service frontlines (Rafaeli et al., 2017), where building rapport in technology-driven encounters has only been implied, but not tested. Our model empirically demonstrates that sRAM is an appropriate framework for this new context that overcomes the limitations of traditional technology acceptance theories. As such, this research takes a significant step forward by providing support for a new way of understanding customer adoption of AI-powered chatbots linked to emotions.

Finally, we extend the sRAM, which examines each dimension/element separately, validating the mederating effects of technology literacy and emotional awareness and the crossover between direct effect, thus unraveling previously unexpected relationships. For example, while the direct effects of social elements on acceptance are significant, the comparison of the combined effects between functional, social, and relational elements result in an absence of significance for social elements. Furthermore, as potential moderators remain under-explored in the existing literature on technology acceptance (Blut et al., 2016), including social robots and AI devices (Heerink et al., 2010; Chi et al., 2020), this study enriches the sRAM by considering the significant role of technology literacy and emotional awareness. Unlike previous research, functional elements and automorphism are not the only variables to generate acceptance from high-tech customers who also prefer high-level emotional, social and relational characteristics for artificial FLE.

Managerial Implications.

Customer acceptance of new technology is one of the key steps to be effectively utilized, however, despite the acclaimed benefits and optimistic forecasts, automated forms of service interaction are not always desired by the customer (Kaplan and Haenlein, 2020). Therefore, managers can use the results of our study to better understand the factors that motivate individuals' use of chatbots in customer service interactions in order to successfully implement such technologies by co-creating value and not destroying it, particularly when addressing the younger generations. The results reveal that the acceptance of chatbots is mainly driven by functional elements such as their usefulness, especially for more advanced users. Consequently, managers should focus on the utilitarian value of cost-effective execution of a wide variety of tasks such as purchasing items, booking appointments, or catering locations (Chattaraman et al., 2019; Robinson et al., 2020). Furthermore, given the significant role of social and relational elements, managers dealing with customer care strategies should also focus on developing trustworthy agents capable of developing human-like conversations and establishing a "bond" with customers, in a way to evoke a sense of social presence, which in turn can generate rapport and trust, commonly associated with satisfaction and loyalty.

Finally, the results show that chatbots are perceived and welcomed in various ways by different customers, based on their preferences and interaction skills, which can be used for segmentation purposes. For users who prefer the personal touch of human interactions, informal and natural dialogues (Guzman, 2019) can contribute to social interactivity, just like with human employees, and thus lead to perceptions of social presence. As users who prefer human-tech interactions seem to be more willing to develop a rapport with chatbots, actions such as emotional recognition, attentive listening, expressing warmth, showing concern for the customer, and understanding the topics can help chatbots to build this rapport (Gremler and Gwinner, 2000). However, despite initial predictions and previous claims, conversational agents who seem too human may not necessarily be accepted by customers and in extreme cases may even dissuade people, especially those less experienced, from using this technology. According to our study, customers will objectify rather than anthropomorphize the chatbot and, therefore, will remain rather indifferent to human characteristics; or they will assume negative attitudes towards them. So, if a service provider is aiming to target customers belonging to the millennial generation, equipping a chatbot with human-like traits may not be the most effective solution and, despite the efforts of firms, it may not pay off. For this reason, the EAI model assumes an interaction between AI FLE and FLE so that the chatbot does not completely replace the human operator but is instead able to determine the exact point where the conversation is becoming an issue and must be diverted to a human operator. The emotional awareness infused in the chatbot through a sentiment analysis algorithm is able to determine this switch point (Lajante and Del Prete, 2020) to make the customer experience pleasant and satisfying. Managers can use the EAI model to operate correct provisioning in automated customer service to realize an omnichannel customer journey. Service managers cannot fail to take into account the weight that emotional recognition has on customer engagement during service encounters and this thesis underlines its importance through a theoretical and empirical path.

Limitations and Future Research.

Given the fact that every individual perceives emotion differently, it is not possible to classify all emotions correctly with only text input and without knowing the full emotional background of the texting person. In this thesis, we relied on chosen scientific psychological concepts for detecting emotions but regarding the emotion extraction model, which can be easily adapted to different psychological approaches and different platforms, more research is needed.

The EAI framework needs more research regarding the interpersonal dimensions of EI, such as empathy or social skills, the same is true for emotion regulation. How to instill empathic skills in a service robot such as a chatbot is still a fragmented field of research, albeit full of perspectives for researchers and scholars.

Always related to the EAI model, the implementation of a sentiment analysis algorithm aimed at detecting the 10 discrete emotions in service encounters could be functional to create chatbots endowed with EI.

Regarding our empirical study, data was collected mainly using a convenience sample, which warrants caution in generalizing the results. Given the exploratory nature of this study, future research should address validity issues with a larger and more representative sample. In addition, the study targeted the millennial generation, who are very different from other cohorts in terms of experience and use of technology. While this is a target of interest, the results should be cross-validated with other age groups. Future researchers may also validate the sRAM with an emotional focus by considering other service robots such as humanoid or embodied forms. This study built on the sRAM and its dimensions, incorporating the moderating role of technology literacy and emotional awareness. However, other moderators such as the other dimensions of EI (i.e., empathy) may prove useful in explaining customer acceptance of chatbots and other automated technologies. Finally, further exploration of the role of perceived humanity, interactivity, and rapport may be a promising avenue for future research on emotions in automated service encounters.

Overall, it is our hope this thesis fosters empirical research on AI and emotions in automated customer service so that researchers, scholars and practitioners work to understand the corresponding opportunities, challenges, and impact on business and people.

REFERENCES

Abbasi, A. S. and Alvi, A. K. (2013), "Impact of employee characteristics and their performance on customer satisfaction", *Science International*, Vol. 25 No. 2, pp. 387–394.

AbuShawar, B. and Atwell, E. (2015), "ALICE Chatbot: Trials & Outputs", *Computación y Sistemas*, Vol. 19.

Adkins, J.H. (2004), *Investigating Emotional Intelligence and Social Skills in Home Schooled Students*, Master's Theses, University of Nevada, Las Vegas.

Adolphs, R. (2002), "Neural systems for recognizing emotion", *Current Opinion in Neurobiology*, Vol. 12 No. 2, pp. 169-177.

Aggarwal, P., Castleberry, S. B., Ridnour, R., and Shepherd, C. D. (2005), "Salesperson empathy and listening: impact on relationship outcomes", *Journal of Marketing Theory and Practice*, Vol. 13 No. 3, pp. 16-31.

Agnihotri, R. and Krush, M. T. (2015), "Salesperson empathy, ethical behaviors, and sales performance: The moderating role of trust in one's manager", *Journal of Personal Selling & Sales Management*, Vol. 35 No. 2, pp. 164–174.

American National Election Studies, University of Michigan, and Stanford University. ANES (2016) Time Series Study. Ann Arbor, MI: Inter-university Consortium for Political and Social Research [distributor], 2017-09-19. https://doi.org/10.3886/ICPSR36824.v2

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*, Vol. 85, pp. 183-189.

Aue, T., and Scherer, KR. (2011), "Effects of intrinsic pleasantness and goal conduciveness appraisals on somatovisceral responding: somewhat similar, but not identical", *Biol. Psychol.*, Vol. 86 No.1, pp. 65–73.

Aziz, Y.A.B. (2008), “The Effects of Emotional Dissonance and Employee’ s Empowerment on Service Quality and Customer Satisfaction Perception: Customer Level Analysis”, *International Journal of Economics and Management*, Vol. 2 No. 2, pp. 237–258.

Badinelli, R., Barile, S., Ng, I., Polese, F., Saviano, M., and Di Nauta, P. (2012), “Viable service systems and decision-making in-service management”, *Journal of Service Management*, Vol. 23 No. 4, pp. 498-526.

Bagdare, S. and Jain, R. (2013), "Measuring retail customer experience", *International Journal of Retail & Distribution Management*, Vol.41 No. 10, pp. 790-804. https://doi.org/10.1108/IJRDM-08-2012-0084

Bagozzi, R. P., Gopinath, M. and Nyer, P. U. (1999). “The role of emotions in marketing.”, *Journal of the Academy of Marketing Science*, Vol. 27 No. 2, pp.184–206.

Barile, S. (2009), “The Dynamic of Informative Varieties in the Processes of Decision Making”. *The 3rd International Conference on Knowledge Generation, Communication and Management*, Orlando, Florida, July 10-13, 2009. Available at SSRN: https://ssrn.com/abstract=1956477

Barile, S., Pels, J., Polese, F., and Saviano, M. (2012a), “An introduction to the viable systems approach and its contribution to marketing”, *Journal of Business Market Management*, Vol.5 No. 2, pp. 54-78.

Barile, S. (Ed.) (2011). *Contributions to theoretical and practical advances in management. A Viable Systems Approach*. International Printing, Avellino.

Barile, S., Saviano, M., and Polese, F. (2014), “Information asymmetry and co-creation in health care services”, *Australasian Marketing Journal* (AMJ), Vol. 22 No.3, pp. 205-217.

Barile, S., and Saviano, M. (2011), *Foundations of systems thinking: the structure-system paradigm, In Barile, S. (Ed.). Contributions to theoretical and practical advances in management. A Viable Systems Approach*. International Printing, Avellino.

Barile, S. and Saviano, M. (2013), “An introduction to a value co-creation model. viability, syntropy and resonance in dyadic interaction”, *Syntropy*, Vol. 2, pp. 69-89.

Barile, S. and Polese, F. (2010), “Linking the viable system and many-to-many network approaches to service-dominant logic and service science”, *International Journal of Quality and Service Sciences*, Vol. 2 No. 1, pp. 23-42.Barile, S. and Saviano, M. (2010), “A new perspective of systems complexity in service science”*, Impresa, Ambiente, Management*, Vol. 4 No. 3, pp. 375 – 414.

Barile, S., Lusch, R., Reynoso, J., Saviano, M., and Spohrer, J. (2016), “Systems, networks, and ecosystems in service research”, *Journal of Service Management*, Vol. 27 No. 4, pp. 652-674.

Barile S., Bassano C., Lettieri M., Piciocchi P., Saviano M. (2020), “Intelligence Augmentation (IA) in Complex Decision Making: A New View of the vSa Concept of Relevance*”*, In: *Spohrer J., Leitner C. (eds) Advances in the Human Side of Service Engineering*. AHFE 2020. Advances in Intelligent Systems and Computing, Vol. 1208. Springer, Cham. https://doi.org/10.1007/978-3-030-51057-2_35

Barros, A., Dumas, M. and Ter Hofstede, A. H. (2005, September). *Service interaction patterns*. *In International Conference on Business Process Management* (pp. 302-318). Springer Berlin Heidelberg, Berlin.

Bassano, C., Barile, S., Saviano, M., Cosimato, S., Pietronudo, M. (2020), “AI technologies & value co-creation in a luxury goods context”, In: *Proceedings of the 53rd Hawaii International Conference on System Sciences | 2020 scholarspace.manoa.hawaii.edu*, pp. 1618-1627.

Beatson, A., Coote, L.V. and Rudd, J.M. (2006), “Determining consumer satisfaction and commitment through self-service technology and personal service usage”, *Journal of Marketing Management*, Vol. 22 No. 7/8, pp. 853-882.

Beer, S. (1984), “The viable system model: Its provenance, development, methodology and pathology”, *Journal of the operational research society*, Vol. 35 No.1, pp. 7-25.

Belanche, D., Casaló, L. V. and Flavián, C. (2019), “Artificial Intelligence in FinTech: Understanding robo-advisors adoption among customers”, *Industrial Management & Data Systems*, Vol. 119 No. 7, pp. 1411–1430.

Bell, D., Gallino, S. and Moreno, A. (2014), “How to win in an omnichannel world”, *MIT Sloan Manage. Rev.*, Vol 56 No.1, pp. 49–53.

Berger, J. (2014), “Word of mouth and interpersonal communication: A review and directions for future research”, *Journal of Consumer Psychology*, Vol. 24, pp. 586–607.

Bettencourt, L. and Gwinner, K. (1996), “Customization of the Service Experience: The Role of the Frontline Employee”, *International Journal of Services Industry Management*, Vol. 7, pp. 2-20. http://dx.doi.org/10.1108/09564239610113442

Bettencourt, L.A., Brown, S.W. and Sirianni, N.J. (2013), “The secret to true service innovation”, *Business Horizon*, Vol. 56 No. 1, pp. 13-22.

Bilgihan, A. (2016), “Gen Y customer loyalty in online shopping: An integrated model of trust, user experience and branding”, *Computers in Human Behavior*, Vol. 61, pp. 103–113.

Bitner, M. J. (1995), “Building service relationships: it's all about promises”, *Journal of the Academy of Marketing Science*, Vol. 23 No. 4, pp. 246-251.

Blom, A. (2017), “Omnichannel-based promotions’ effects on purchase behavior and brand image”, *Journal of Retailing and Consumer Service.* http://dx.doi.org/10.1016/j.jretconser.2017.08.008

Blut, M., Wang, C., and Schoefer, K. (2016), “Factors influencing the acceptance of self-service technologies: A meta-analysis”, *Journal of Service Research*, Vol. 19 No. 4, pp. 396-416.

Bolton, R. N., McColl-Kennedy, J.R., Cheung, L., Gallan, A., Orsinger, C., Witell, L. and Zaky, M. (2018), "Customer experience challenges: bringing togheter digital, physical and social realms", *Journal of Service Management*, Vol. 29 No. 5, pp. 776-808.

Booth, A., Papaioannou, D. and Sutton, A. (2012). *Systematic approaches to a successful literature review*. London: SAGE Publications.

Braun, A. (2003), *Chatbots in der Kundenkommunikation*, Axel Springer Verlag, Berlin.

Breazeal, C. (2003), "Toward sociable robots", *Robotics and autonomous systems*, Vol. 42 No. 3-4, pp. 167-175.

Breidbach, C. F., Brodie, R., and Hollebeek, L. (2014), "Beyond virtuality: from engagement platforms to engagement ecosystems", *Managing Service Quality*, Vol. 24 No. 6, pp. 592-611.

Brief, A. P., and Motowidlo, S. J. (1986), "Prosocial organizational behaviors", *Academy of Management Review*, Vol. 11 No. 4, pp. 710-725.

Briscoe, G., Keränen, K. and Parry, G. (2012), "Understanding complex service systems through different lenses: an overview", *European Management Journal*, Vol. 30 No. 5, pp. 418-426.

Brodie, R. J., Hollebeek, L. D., Jurić, B. and Ilić, A. (2011), "Customer Engagement: Conceptual Domain, Fundamental Propositions, and Implications for Research", *Journal of Service Research*, Vol. 14 No. 3, pp. 252–271.

Brynjolfsson, E., Hu, Y.J. and Rahman, M.S. (2013) "Competing in the Age of Omnichannel Retailing", *MIT Sloan Manag. Rev.,* Vol. 54, pp. 23–29.

Byrne, K. (2018), "Chatbots: Your new best friend?", Retrieved from https://www.

independent.ie/life/chatbots-your-new-best-friend-37023285.html.

Čaić, M., Odekerken-Schröder, G. and Mahr, D. (2018), "Service robots: value co-creation and co-destruction in elderly care networks", *Journal of Service Management*, Vol. 29 No. 2, pp. 178-205.

Carter, C.S., and Porges, S.W., (2011), *The neurobiology of social bonding and attachment*. In J. Decety and J.T. Cacioppo (eds.), The oxford handbook of social neuroscience (pp. 151-163), Oxford University Press, New York.

Chandler, J.D. and Lusch, R.F. (2015), "Service systems: a broadened framework and research agenda on value propositions, engagement, and service experience", *Journal of Service Research*, Vol. 18 No. 1, pp. 6-22.

Chandler, J., Rosenzweig, C. and Moss, A.J. (2019), "Online panels in social science research: Expanding sampling methods beyond Mechanical Turk", *Behav Res,* Vol. 51, pp. 2022–2038. https://doi.org/10.3758/s13428-019-01273-7

Chattaraman, V., Kwon, W., Gilbert, J., and Ross, K. (2019), "Should AI-Based, conversational digital assistants employ social-or task-oriented interaction style? A task-competency and reciprocity perspective for older adults", *Computers in Human Behavior*, Vol. 90, pp. 315–330.

Chi, O., Denton, G., and Gursoy, D. (2020), "Artificially intelligent device use in service delivery: A systematic review, synthesis, and research agenda", *Journal of Hospitality Marketing & Management*. https://doi.org/10.1080/19368623.2020.1721394.

Ciarrochi, J., Forgas, J.P. and Mayer, J.D. (2001), *Emotional Intelligence in Everyday Life: A Scientific Inquiry*, Psychology Press: London, UK.

Cohen, J., and Areni, C. (1991), *Affect and consumer behavior*. In T. S. Robertson & H. H. Kassarjian (Eds.), Handbook of consumer behavior (pp. 188–240). Englewoord Cliffs: Prentice-Hall.

Cohn, M.A., Fredrickson, B.L., Brown, S.L., Mikels, J.A. and Conway, A.M. (2009), "Happiness unpacked: Positive emotions increase life satisfaction by building resilience", *Emotion 2009*, Vol. 9, pp. 361–368.

Collier, J.E. and Kimes, S.E. (2013), “Only if it is Convenient: Understanding How Convenience Influences Self-Service Technology Evaluation”, *Journal of Service Research,* Vol. 16 N.1, pp. 39-51.

Coulter, R. A., and Ligas, M. (2004), “A typology of customer-service provider relationships: the role of relational factors in classifying customers”, *Journal of Services Marketing*, Vol. 18 No. 6, pp. 482-493.

Dabholkar, P., Michelle Bobbitt, L. and Lee, E. (2003), "Understanding consumer motivation and behavior related to self-scanning in retailing", *International Journal of Service Industry Management*, Vol. 14 No. 1, pp. 59-95.

Dahl, D. W., Honea, H. and Manchanda, R. V. (2003), “The nature of self- reported guilt in consumption contexts”, *Marketing Letters*, Vol. 14 No. 3, pp. 159– 171.

Dallimore, K. S., Sparks, B. A., and Butcher, K. (2007), “The influence of angry customer outbursts on service providers' facial displays and affective states”, *Journal of Service Research*, Vol. 10 No. 1, pp. 78–92.

Damasio, A. R. (1996), “The somatic marker hypothesis and the possible functions of the prefrontal cortex”, *Philosophical Transactions of the Royal Society of London. Series B: Biological Sciences*, Vol. 351 No. 1346, pp. 1413-1420.

Davis, F.D. (1989), “Perceived usefulness, perceived ease of use, and user acceptance of information technology”, *MIS Quarterly*, Vol. 13 No. 3, pp. 318-340.

Daus, C. S., and Cage, T. G. (2008), *Learning to face emotional intelligence:Training and workplace applications*, Northampton, MA: Edward Elgar.

Dempt, F. (2016), “Futuregram”, available at: http://futuregram.trendone.com/index.html#einstieg (accessed June 24, 2017).

Decker, M., Fischer, M., and Ott, I. (2017), "Service Robotics and Human Labor: A first technology assessment of substitution and cooperation", *Robotics and Autonomous Systems,* Vol. 87, pp. 348-354.

De Keyser, A., Köcher, S., Alkire (née Nasr), L., Verbeeck, C. and Kandampully, J. (2019), "Frontline Service Technology infusion: conceptual archetypes and future research directions", *Journal of Service Management*, Vol. 30 No. 1, pp. 156-183.

Dennis, C. (2005), *Objects of Desire: Consumer Behaviour in Shopping Centre Choice*, Palgrave, London.

Drollinger, T. and Comer, L.B. (2013), "Salesperson's listening ability as an antecedent to relationship selling", *Journal of Business & Industrial Marketing*, Vol. 28 No. 1, pp. 50–59.

Duffy, B. (2003), "Anthropomorphism and the social robot. Robotics and Autonomous Systems", Vol. 42 No. 3/4, pp. 177–190.

Dwivedi, Y., Rana, N., Jeyaraj, A., Clement, M. and Williams, M. (2019), "Re-examining the unified theory of acceptance and use of technology (UTAUT): Towards a revised theoretical model", *Information Systems Frontiers*, Vol. 21 No. 3, pp. 719–734.

Eisenberg, N.I., (2016), *Social pain and social pleasure: Two overlooked but fundamental mammalian emotions?* in Feldman-Barrett, L., Lewis, M. and Haviland-Jones, J.M. (Eds), Handbook of Emotions, pp. 440-452, The Guilford Press, New York.

Eisingerich, A. B., Helen Chun, H., Liu, Y., Jia, H. and Bell, S. J. (2015), "Why recommend a brand face-to-face but not on Facebook? How word-of-mouth on online social sites differs from traditional word- of-mouth", *Journal of Consumer Psychology*, Vol. 25, pp. 120–128.

Ellsworth, P. C. and Scherer, K. R. (2003), *Appraisal processes in emotion*, In R. J. Davidson, K. R. Scherer, & H. H. Goldsmith (Eds.), Handbook of affective sciences (pp. 572–595), New York: Oxford University Press.

Epley, N., Akalis, S., Waytz, A. and Cacioppo, J. (2008), "Creating Social Connection Through Inferential Reproduction", *Psychological Science*, Vol. 19 No. 2, pp. 114–120.

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

Espejo, R. (1996), "Requirements for effective participation in self-constructed organizations", *European Management Journal*, Vol. 14 No. 4, pp. 414-422.

Espejo, R. and Harnden, R. (Eds.). (1989), *The viable system model: interpretations and applications of Stafford Beer's VSM*, Wiley, Chichester.

Espejo, R., and Reyes, A. (2011), *Organizational systems: Managing complexity with the viable system model.* Springer Science & Business Media, New York.

Espejo, R. (1990), "The viable system model. Systemic Practice and Action Research", Vol. 3 No. 3, pp. 219-221.

Ekman, P., Levenson, R. W. and Friesen, W. V. (1983), "Autonomic nervous system activity distinguishes among emotions", *Science*, Vol. 221, pp. 1208–1210.

Epley, N., Akalis, S., Waytz, A. and Cacioppo, J. (2008), "Creating Social Connection Through Inferential Reproduction", *Psychological Science*, Vol. 19 No. 2, pp. 114–120.

Fernández-Berrocal, P. and Extremera, N. (2006), "Emotional intelligence: a theoretical and empirical review of its first 15 years of history", *Psicothema*, Vol. 18, pp. 7–12.

Fernandes, T. and Pedroso, R. (2017), "The effect of self-checkout quality on customer satisfaction and repatronage in a retail context," *Service Business*, Vol. 11, pp. 69–92.

Finn, A. (2005), "Reassessing the foundations of customer delight", *Journal of Service Research*, Vol. 8, pp. 103–116.

Fiske, S., Cuddy, A. and Glick, P. (2007), "Universal dimensions of social cognition: Warmth and competence", *Trends in Cognitive Science*, Vol. 42 No. 11, pp. 77–83.

Fitzsimmons, J. A. and Fitzsimmons, M. J. (1994), *Service management for competitive advantage*, McGraw- Hill, New York.

Fong, T., Nourbakhsh, I.R. and Dautenhahn, K. (2003), "A survey of socially interactive robots", *Robotics and Autonomous Systems*, Vol. 42, pp. 143-166.

Forbes (2018), "10 Customer Experience Implementations of Artificial Intelligence", Retrieved July 21, 2020 from https://www.forbes.com/sites/blakemorgan/2018/ 02/08/10-customer-experience-implementations-of-artificial-intelligence.

Ford, B. Q. and Gross, J. J. (2018), "Emotion regulation: Why beliefs matter", *Canadian Psychology*, Vol. 59, pp. 1–15.

Fornell, C., Johnson, M. D., Anderson, E. W., Cha, J. and Everitt Bryant, B. (1996), "Growing the trust relationship" [Electronic version], *Journal of Marketing*, Vol. 60 No. 4, pp. 7-18.

Frey, C. B., and Osborne, M. A. (2017), "The future of employment: how susceptible are jobs to computerisation?", *Technological Forecasting and Social Change*, Vol. 114, pp. 254-280.

Frijda, N. H. (1993), *Moods, emotion episodes, and emotions*, M. Lewis & J. M. Haviland (Eds.), Handbook of emotions, pp. 381-403, Guilford Press.

Frijda, N. H., Kuipers, P. and ter Schure, E. (1989), "Relations among emotion, appraisal, and emotional action readiness", *Journal of Personality and Social Psychology*, Vol. 57 No. 2, pp. 212–228. https://doi.org/10.1037/0022-3514.57.2.212

Frijda N.H., and Scherer, K.R. (2009), *Emotion definitions (psychological perspectives)*, In Oxford Companion to Emotion and the Affective Sciences, ed. D Sander, KR Scherer, pp. 142–44. Oxford, UK: Oxford Univ. Press

Gabbott, M. and Hogg, G. (2001), "The role of non-verbal communication in service encounters: A conceptual framework", *Journal of Marketing Management*, Vol. 17 No. 1–2, pp. 5–26.

Gardner, H. and Hatch, T. (1989), "Educational Implications of the Theory of Multiple Intelligences", *Educational Researcher*, Vol. 18, pp. 4–10.

Gelderman, C., Ghijsen, P. and van Diemen, R. (2011), “Choosing self-service technologies or interpersonal services – the impact of situational factors and technology-related attitudes”, *Journal of Retailing and Consumer Services*, Vol. 18 No. 5, pp. 414–421.

Gentsch K., Grandjean D. and Scherer K.R. (2014), “Coherence explored between emotion components: evidence from event-related potentials and facial electromyography”, *Biol. Psychol.*, Vol. 98, pp. 70–81.

Gerlach, G. I., Rödiger, K., Stock, R. M., and Zacharias, N. A. (2016), “Salespersons’ empathy as a missing link in the customer orientation–loyalty chain: an investigation of drivers and age differences as a contingency”, *Journal of Personal Selling & Sales Management*, Vol. 36 No. 3, pp. 221-239.

Gilmore, S. (1988), “Schools of Activity and Innovation”, *The Sociological Quarterly*, Vol. 29 No. 2, pp. 203-219, DOI: 10.1111/j.1533-8525.1988.tb01251.x

Goleman, D. (1995), *Emotional intelligence*, Bantam Books, New York.

Goleman, D. (1998), *Working with Emotional Intelligence*; Bantam Books, New York.

Goleman, D. (2001), *An EI-based theory of performance. In the Emotionally Intelligent Workplace: How to Select for, Measure, and Improve Emotional Intelligence in Individuals, Groups, and Organizations*, Vol. 1, pp. 27–44, John Wiley & Sons: Hoboken, NJ, USA.

Golinelli, G. M. (2010), *Viable systems approach (VSA): Governing business dynamics*. Cedam, Padova.

Gorry, G. A. and Westbrook, R. A. (2011), “Once more, with feeling: Empathy and technology in customer care”, *Business Horizons*, Vol. 54 No. 2, pp. 125–134.

Gosling, S. D. and Mason, W. (2015), “Internet research in psychology”, *Annual Review of Psychology*, Vol. 66, pp. 877–902. https://doi.org/10. 1146/annurev-psych-010814-015321

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*, Vol. 46 No. 1, pp. 86–96. https://doi.org/10.2307/30040678

Grappi, S., Romani, S. and Bagozzi, R. P. (2015), “Consumer stakeholder responses to reshoring strategies”, *Journal of the Academy of Marketing Science*, Vol. 43, pp. 453–471.

Gray H. M., Gray K. and Wegner D. M, (2007), “Dimensions of mind perception”, *Science*, pp. 315-619.

Gremler, D. and Gwinner, K. (2000), “Customer-Employee Rapport in Service Relationships”, *Journal of Service Research*, Vol. 3 No. 1, pp. 82–104.

Gresham, F.M., Elliott, S.N., Vance, M.J. and Cook, C.R. (2011), “Comparability of the Social Skills Rating System to the Social Skills Improvement System: Content and psychometric comparisons across elementary and secondary age levels”, *School Psychology Quarterly*, Vol. 26, pp. 27–44.

Grewal, D., Roggeveen, A. L., and Nordfält, J. (2017), “The future of retailing”, *Journal of Retailing*, Vol. 93 No. 1, pp. 1-6.

Griol, D., Carbó, J. and Molina, J. M. (2013), “An automatic dialog simulation technique to develop and evaluate interactive conversational agents”, *Applied Artificial Intelligence*, Vol. 27, pp.759-780.

Grönroos, C. (2007), *Service management and marketing: customer management in service competition*, John Wiley & Sons.

Gross, J. J. (2015a), “Emotion regulation: Current status and future Prospects”, *Psychological Inquiry*, Vol. 26 No. 1, pp. 1–26.

Grougiou, V. and Pettigrew, S. (2011), “Senior customers' service encounter preferences”, *Journal of Service Research*, Vol. 14 No. 4, pp. 475–488.

Gutek, B. A., Groth, M. and Cherry, B. (2002), "Achieving service success through relationships and enhanced encounters", *Academy of Management Perspectives*, Vol.16 No. 4, pp. 132–144.

Guthrie, S.E. (1993). *Faces in the clouds: A new theory of religion*. New York: Oxford University Press.

Guzman, A. (2019), "Voices in and of the machine: Source orientation toward mobile virtual assistants", *Computers in Human Behavior*, Vol. 90, pp. 343–350.

Han, S., Lerner, J. S. and Keltner, D. (2007), "Feelings and consumer decision making: the appraisal-tendency framework", *Journal of Consumer Psychology*, Vol.17, pp.158–168.

Heerink, M., Kröse, B., Evers, V. and Wielinga, B. (2010), "Assessing acceptance of assistive social agent technology by older adults: the Almere Model", *International Journal of Social Robots*, Vol. 2 No. 4, pp. 361-375.

Hennig-Thurau, T., Groth, M., Paul, M., and Gremler, D. D. (2006), "Are all smiles created equal? How emotional contagion and emotional labor affect service relationships", *Journal of Marketing*, Vol. 70 No. 3, pp. 58-73.

Holz, T., Dragone, M. and O'Hare, G.M. (2009), "Where Robots and Virtual Agents Meet", *International Journal of Social Robotics,* Vol. 1, pp. 83-93.

Homburg, C., Wieseke, J. and Hoyer, W.D. (2009), "Social identity and the service-profit chain." *Journal of Marketing,* Vol. 73, pp. 38–54.

Huang, M. H., and Rust, R. T. (2018), "Artificial intelligence in service", *Journal of Service Research*, Vol. 21 No. 2, pp. 155-172.

Hulland, J. and Miller, J. (2018), "Keep on Turkin?", *J. of the Acad. Mark. Sci*., Vol. 46, pp. 789–794. https://doi.org/10.1007/s11747-018-0587-4

Hyken, S. (2017b), “AI and Chatbots are transforming the customer experience”. July 15 https://www.forbes.com/sites/shephyken/2017/07/15/ai-and-chatbots-are-transforming-the-customer-experience/#1cad7b5741f7.

Ioannidou, F. and Konstantikaki, V. (2008), “Empathy and emotional intelligence: What is really about?”, *International Journal of Caring Sciences*, Vol. 1, p. 118.

Jayanti, R. (1996), “Affective responses towards service providers: implications for service encounter satisfaction”, *Health Marketing Quarterly*, Vol. 14 No. 1, pp. 49-65.

Jin, B. and Sternquist, B. (2004), "Shopping is truly a joy”, The *Service Industries Journal, Taylor & Francis Journals*, Vol. 24 No. 6, pp. 1-18.

Johnson, M., and Zinkhan, G. M. (1991), “Emotional responses to a professional service encounter”, *Journal of Services Marketing*, Vol. 5 No. 2, pp. 5-16.

Jordan, S., Haidegger, T., Kovacs, L., Felde, I. and Rudas, I. (2013), “The rising prospects of cloud robotic applications”, in *Computational Cybernetics (ICCC), 2013 IEEE 9th International Conference,* Tihany, Hungary, pp. 327-332.

Jörling, M., Böhm, R. and Paluch, S. (2019), “Service Robots: Drivers of Perceived Responsibility for Service Outcomes”, *Journal of Service Research*.

Juaneda-Ayensa, E., Mosquera, A. and Sierra Murillo, Y. (2016), “Omnichannel customer behavior: key drivers of technology acceptance and use and their effects on purchase intention”, *Frontiers in Psychology*, Vol. 7 No. 1117, pp. 1-11.

Kaplan, L. B., Szybillo, G. J. and Jacoby, J. (1974), “Components of perceived risk in product purchase: a cross-validation”, *Journal of Applied Psychology*, Vol. 59, pp. 287–291.

Kaplan, A. and Haenlein, M. (2020), “Rulers of the world, unite! The challenges and opportunities of artificial intelligence”, *Business Horizons*, Vol. 63 No.1, pp. 37–50.

Kasnakoglu, B. T., Yilmaz, C., and Varnali, K. (2016), “An asymmetric configural model approach for understanding complainer emotions and loyalty”, *Journal of Business Research*, Vol. 69 No. 9, pp. 3659-3672.

Keltner, D. and Horberg, E. J. (2015), *Emotion-cognition interactions*, In: APA handbook of personality and social psychology, volume 1: attitudes and social cognition, pp. 623–664, Washington, DC: American Psychological Association.

Kernbach, S., and Schutte, N. S. (2005), “The impact of service provider emotional intelligence on customer satisfaction”, *Journal of Services Marketing*, Vol. 19 No. 7, pp. 438-444.

Kleijnen, M., Lee, N., and Wetzels, M., (2009), "An exploration of consumer resistance to innovation and its antecedents", *Journal of Economic Psychology*, Vol. 30 No. 3, pp. 344-357.

Kielser, S., and Hinds, P. (2004), “Introduction to this special issue on human-robot interaction”, *Human-Computer Interaction,* Vol. 19 No. 1-2, pp. 1-8.

Kim, S., Schmitt, B. and Thalman, N. (2019), “Eliza in the uncanny valley: Anthropomorphizing consumer robots increases their perceived warmth but decreases liking”, *Marketing Letters*, Vol. 30 No. 1, pp. 1–12.

Koole, S. L. (2009), “The psychology of emotion regulation: An integrative review”, *Cognition and Emotion*, Vol. 23 No.1, pp. 4–41.

Kranzbühler, A., Zerres, A. and Kleijnen, M.H.P. (2020), “Beyond valence: a meta-analysis of discrete emotions in firm-customer encounters”, *J. of the Acad. Mark. Sci,* Vol. 48, pp. 478–498. https://doi.org/10.1007/s11747-019-00707-0

Kumar, A., and Telang, R. (2012), “Does the Web Reduce Customer Service Cost? Empirical Evidence from a Call Center”, *Information Systems Research*, Vol. 23, pp. 721-737.

Lajante M. (2019), “Augmented empathic capacity: An integrative framework for supporting customer engagement throughout the automated customer journey”, In F.J. Martinez-Lopez, J.C. Gazquèz-Abad and A. Roggeveen (eds.): *Advances in National Brand and Private Label*, Vol. 6, pp. 121-129, Springer.

Lajante, M. and Del Prete, M. (2020), “Technology-infused Organizational Frontlines: When (Not) to Use Chatbots in Retailing to Promote Customer Engagement”, Pantano, E. (Ed.) *Retail*

Futures, pp. 71-84, Emerald Publishing Limited. https://doi.org/10.1108/978-1-83867-663-620201011

Larivière, B., Bowen, D., Andreassen, T. W., Kunz, W., Sirianni, N. J., Voss, C., ... and De Keyser, A. (2017), "Service Encounter 2.0": An investigation into the roles of technology, employees and customers", *Journal of Business Research*, Vol. 79, pp. 238-246.

Laroche, M., Ueltschy, L.C., Abe, S., Cleveland, M. and Yannopoulos, P. (2004), "Service quality perceptions and customer satisfaction: Evaluating the role of culture", *Journal of International Marketing*, Vol. 12 No. 3, pp. 58–85.

Laros, F. J. M. and Steenkamp, J. B. (2005), "Emotions in consumer behavior: a hierarchical approach", *Journal of Business Research*, Vol. 58, pp. 1437–1445.

Lazarus, R. S. (1991), "Cognition and motivation in emotion", *American Psychologist*, Vol. 46, pp. 352–367.

Lee, Y. H. and Ching Lim, E. A. (2010), "When good cheer goes unrequited: How emotional receptivity affects evaluation of expressed emotion", *Journal of Marketing Research*, Vol. 47 No. 6, pp. 1151–1161.

Lee, S., Comer, L. B., Dubinsky, A. J. and Scbafer, K. (2011), "The role of emotion in the relationship between customers and automobile salespeople", *Journal of Managerial Issues*, Vol. 23 No. 2, pp. 206–226.

Lemon, K. N. and Verhoef, P. C. (2016), "Understanding Customer Experience Throughout the Customer Journey", *Journal of Marketing*, Vol. 80 No. 6, pp. 69-96.

Lench, H. C., Flores, S. A. and Bench, S. W. (2011), "Discrete emotions predict changes in cognition, judgment, experience, behavior, and physiology: a meta- analysis of experimental emotion elicitations", *Psychological Bulletin*, Vol. 137, pp. 834-855.

Leyens, J.P., Cortes, B.P., Demoulin, S., Dovidio, J., Fiske, S.T. and Gaunt, R. (2003), "Emotional prejudice, essentialism, and nationalism", *European Journal of Social Psychology*, Vol. 33, pp. 703–717.

Lerner, J. S. and Keltner, D. (2000), “Beyond valence: Toward a model of emotion-specific influences on judgement and choice”, *Cognition and Emotion*, Vol. 14 No. 4, pp. 473–493. https://doi.org/10.1080/026999300402763

Lerner, J. S. and Keltner, D. (2001), “Fear, anger and risk”, *Journal of Personality and Social Psychology*, Vol. 81, pp. 146–159.

Lerner, J. S., Gonzalez, R. M., Small, D. A. and Fischhoff, B. (2003), “Effects of fear and anger on perceived risks of terrorism: a national field experiment”, *Psychological Science*, Vol. 14, pp. 144–150.

Liao, H. and Chuang, A. (2007), “Transforming service employees and climate: A multilevel, multisource examination of transformational leadership in building long-term service relationships”, *Journal of Applied Psychology*, Vol. 92 No. 4, p. 1006.

Liébana-Cabanillas, F., Sánchez-Fernández, J. and Muñoz-Leiva, F. (2014), “Antecedents of the adoption of the new mobile payment systems: The moderating effect of age”, *Computers in Human Behavior*, Vol. 35, pp. 464–478.

Lim, E. A. C., Lee, Y. H. and Foo, M. D. (2017), “Frontline employees' nonverbal cues in service encounters: A double-edged sword”, *Journal of the Academy of Marketing Science*, Vol. 45 No. 5, pp. 657–676.

Lin, J. S. C., and Lin, C. Y. (2011), “What makes service employees and customers smile: Antecedents and consequences of the employees' affective delivery in the service encounter”, *Journal of Service Management*, Vol. 22 No. 2, pp. 183-201.

Lin, H., Chi, O. H., & Gursoy, D. (2019), “Antecedents of customers’ acceptance of artificially intelligent robotic device use in hospitality services”, *Journal of Hospitality Marketing & Management*, Vol. 29 No. 5, pp. 530–549.

Lloyd, A. E. and Luk, S. T. (2011), “Interaction behaviors leading to comfort in the service encounter”, *Journal of Services Marketing*, Vol. 25 No. 3, pp.176–189.

Lopes, P.N., Brackett, M.A., Nezlek, J., Schütz, A., Sellin, I. and Salovey, P. (2004). "Emotional intelligence and social interaction", *Personality and Social Psychology Bulletin*, Vol. 30, pp. 1018-1034.

Lopes, P.N., Salovey, P., Côté, S. and Beers, M. (2005), "Emotion regulation ability and the quality of social interaction", *Emotion*, Vol. 5, pp. 113-118.

Lu, T., Tu, R. and Jen, W. (2011), "The role of service value and switching barriers in an integrated model of behavioural intentions", *Total Quality Management*, Vol. 22 No. 10, pp. 1071–1089.

Lu, V., Wirtz, J., Kunz, W., Paluch, S., T Martins, A. and Patterson, P. (2020), "Service robots, customers, and service employees: what can we learn from the academic literature and where are the gaps?", *Journal of Service Theory & Practice*, Vol. 30 No. 3, pp. 361-391.

Lusch, R.F., & Vargo, S. L. (2014), *Service dominant logic: Premises, perspectives and possibilities*, Cambridge: Cambridge University Press.

Magids, S., Zorfas, A. and Leemon, D. (2015), "The new science of customer emotions", *Harvard Business Review*, Vol. 76, pp. 66-74.

Malthouse, E. C., and Calder, B. J. (2011), "Comment: engagement and experiences: comment on Brodie, Hollenbeek, Juric, and Ilic (2011)", *Journal of Service Research*, Vol. 14 No. 3, pp. 277-279.

Mars, M., Bronstein, J., & Lusch, R. (2012), "The value of a metaphor: Organizations and ecosystems", *Organizational Dynamics*, Vol. 41 No. 2, pp. 278-297.

Mattila, A. S. and Enz, C. A. (2002), "The role of emotions in service encounters", *Journal of Service Research*, Vol. 4 No. 4, pp. 268-277.

Mayer, J. D. and Salovey, P. (1997), *What is emotional intelligence?* In P. Salovey & D. J. Sluyter (Eds.), Emotional development and emotional intelligence: Educational implications, pp. 3–34, Basic Books.

Mayer, J.D., Salovey, P., Caruso, D.R. and Sitarenios, G. (2003), "Measuring emotional intelligence with the MSCEIT V2. 0.", *Emotion*, Vol. 3, pp. 97–105.

Medler-Liraz, H. (2016). The role of service relationships in employees' and customers' emotional behavior, and customer-related outcomes. Journal of Services Marketing, 30(4), 437–448.

Melero, I., Javier Sese, F. and Verhoef, P.C. (2016), "Redefiniendo la experiencia del cliente en el entornoomnicanal",*Universia Business Review*, Vol. 13 No. 2, pp. 18-37

Mende, M., Scott, M., van Doorn, J., Grewal, D. and Shanks, I. (2019), "Service Robots Rising: How Humanoid Robots Influence Service Experiences and Elicit Compensatory Consumer Responses", *Journal of Marketing Research*, Vol. 56 No. 4, pp. 535–556.

Menon, K., and Dubé, L. (2000), "Ensuring greater satisfaction by engineering salesperson response to customer emotions", *Journal of Retailing*, Vol. 76 No. 3, pp. 285-307.

Meuter, M. L., Bitner, M. J., Ostrom, A. L. and Brown, S. W. (2005), "Choosing among alternative service delivery modes: An investigation of customer trial of self-service technologies", *Journal of Marketing*, Vol. 69 No. 2, pp. 61–83.

McLean, G. and Osei-Frimpong, K. (2019), "Hey Alexa...examine the variables influencing the use of artificial intelligent in-home voice assistants", *Computers in Human Behavior*, Vol. 99, pp. 28–37.

Miller, K., Birkholt, M., Scott, C. and Stage, C. (1995), "Empathy and burnout in human service work: An extension of a communication model", *Communication Research*, Vol. 22 No. 2, pp. 123-147.

Miller, J. D., Crowe, M., Weiss, B., Maples-Keller, J. L. and Lynam, D. R. (2017), "Using online, crowdsourcing platforms for data collection in personality disorder research: The example of Amazon's Mechanical Turk", *Personality Disorders: Theory, Research, and Treatment*, Vol. 8 No.1, pp. 26–34. https://doi.org/10.1037/per0000191

Miyazaki, A. D., Lassar, W. M. and Taylor, K. A. (2007), "Hispanic vs non-Hispanic response to online self-service tasks: Implications for perceived quality and patronage intentions", *Journal of Services Marketing*, Vol. 21 No. 7, pp. 520–529.

Moe, W.W. and Schweidel, D.A. (2012), "Online Product Opinions: Incidence, Evaluation, and Evolution", *Marketing Science,* Vol. 31, pp. 372-386.

Mori, M. (2012), "The Uncanny Valley", Retrieved from https://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=6213238.

Mosquera, A., Olarte Pascual, C. and Juaneda Ayensa, E. (2017), "Understanding the customer experience in the age of omni-channel shopping", *Icono 14*, Vol. 15 No. 2, pp. 166-185. doi: 10.7195/ri14.v15i2.1070

Mulligan, K. and Scherer, K.R. (2012), "Toward a working definition of emotion", *Emot. Rev.,* Vol. 4 No. 4, pp. 345–57.

Murphy, J., Hofacker, C., and Gretzel, U. (2017), "Dawning of the age of robots in hospitality and tourism: challenges for teaching and research", *European Journal of Tourism Research*, Vol. 15, pp. 104-111.

Neisser, U. (1967), *Cognitive psychology*, Appleton-Century-Crofts, New York.

Nomura, T., Kanda, T., and Suzuki, T. (2006), "Experimental investigation into influence of negative attitudes toward robots on human–robot interaction", *AI & Society*, Vol. 20 No. 2, pp. 138-150.

Norman, D.A. (1998), *The design of everyday things*, Basic Books, New York.

Nunnally, J. (1978), *Psychometric theory*, New York: McGraw-Hill.

Ormerod, P. (2011), *Butterfly economics: A new general theory of social and economic behavior*, New York, NY: Pantheon Books.

Ostrom, A. L., Parasuraman, A., Bowen, D. E., Patrício, L., and Voss, C. A. (2015), "Service research priorities in a rapidly changing context", *Journal of Service Research*, Vol. 18 No. 2, pp. 127-159.

Ou, Y. C. and Verhoef, P. C. (2017), "The impact of positive and negative emotions on loyalty intentions and their interactions with customer equity drivers", *Journal of Business Research*, Vol. 80, pp. 106–115.

Qiu, H., Li, M., Shu, B. and Bai, B. (2020), “Enhancing hospitality experience with service robots: The mediating role of rapport building”, *Journal of Hospitality Marketing & Management*, Vol. 29 No.3, pp. 247–268.

Osburg, V.-S., Strack, M., Conroy, D. M., & Toporowski, W. (2017), “Unveiling ethical product features: The importance of an elaborated information presentation”, *Journal of Cleaner Production*, Vol. 162, pp. 1582–1591.

Pagallo, U. (2013), “Robots in the cloud with privacy: a new threat to data protection”, *Computer Law & Security Review*, Vol. 29 No. 5, pp. 501-508.

Pansari, A., and Kumar, V. (2017), “Customer engagement: the construct, antecedents, and consequences”, *Journal of the Academy of Marketing Science*, Vol. 45 No. 3, pp. 294-311.

Parasuraman, A., Zeithaml, V. A., and Berry, L. L. (1985), “A conceptual model of service quality and its implications for future research”, *Journal of Marketing*, Vol. 49 No. 4, pp. 41-50.

Patrício, L., Fisk, R.P., Cunha, J.F. and Constantine, L. (2011), “Multilevel service design: From customer value constellation to service experience blueprint”, *Journal of Service Research*, Vol. 14 No. 2, pp. 180-200.

Patterson, P. (2016), “Retrospective: Tracking the impact of communications effectiveness on client satisfaction, trust and loyalty in professional services”, *Journal of Services Marketing*, Vol. 30 No. 5, pp. 485–489.

Patwardhan, H. and Balasubramanian, S.K. (2011), "Brand romance: a complementary approach to explain emotional attachment toward brands", *Journal of Product & Brand Management*, Vol. 20 No. 4, pp. 297-308. https://doi.org/10.1108/10610421111148315

Peer, E., Vosgerau, J. and Acquisti, A. (2014), “Reputation as a sufficient condition for data quality on Amazon Mechanical Turk.” *Behavior Research Methods*, Vol. 46, pp. 1023–1031. https://doi.org/10.3758/s13428- 013-0434-y

Pérez, J.C., Petrides, K.V. and Furnham, A. (2005), *Measuring trait emotional intelligence,* In Emotional Intelligence: An International Handbook, pp. 181–201, Hogrefe & Huber Publishers, Ashland, USA.

Picot-Coupey, K., Huré, E. and Piveteau, L. (2016), "Channel design to enrich customers'shopping experiences", *International Journal of Retail and Distribution Management*, Emerald, Vol. 44 No. 3, pp. 336-368.

Pieska, S., Luimula, M., Jauhiainen, J. and Spiz, V. (2013). "Social service robots in wellness and restaurant applications", *Journal of Communication and Computer*, Vol. 10, pp.116-123.

Piotrowicz, W. and Cuthbertson, R. (2014), "Introduction to the special issue information technology in retail: toward omnichannel retailing", *International Journal of Electronic Commerce*, Vol. 18 No. 4, pp. 5–16.

Polese F., Caputo F., Carrubbo L. and Sarno D. (2016), *The value (co)creation as peak of social pyramid*. In Russo- Spena T., Mele C. (eds.), Proceedings 26th Annual RESER Conference, "What's ahead in service research: new perspectives for business and society", pp. 1232-1248, RESER, University of Naples "Federico II".

Podsakoff P.M., MacKenzie S.B., Podsakoff N.P. (2012), "Sources of method bias in social science research and recommendations on how to control it", *Annual Review of Psychology*, Vol. 63, pp. 539-569. DOI: 10.1146/annurev-psych-120710-100452.

Pounders, K.R., Moulard, J.G. and Babin, B.J. (2018), "Examining customer-created guilt in a service context", *Psychol Mark.*; Vol. 35, pp. 830– 844. https://doi.org/10.1002/mar.21138

Price, L. L., Arnould, E. J. and Deibler, S. L. (1995), "Consumers' emotional responses to service encounters: the influence of the service provider", *International Journal of Service Industry Management*, Vol. 6 No. 3, pp. 34-63.

Puccinelli, N. M., Grewal, D., Motyka, S., Andrzejewski, S. A. and Avnet, T. (2016), "Effects of affect on consumer behavior: a meta-analytic integration", *Marketing Science Institute Working Paper Series*, Report No. 16, p. 114.

Pugh, S. D. (2001), “Service with a smile: emotional contagion in the service encounter”, *Academy of Management Journal*, Vol. 44, pp. 1018– 1027.

Rafaeli, A., Altman, D., Gremler, D. D., Huang, M. H., Grewal, D., Iyer, B. and de Ruyter, K. (2017), “The future of frontline research: Invited commentaries”, *Journal of Service Research*, Vol. 20 No.1, pp. 91–99.

Ravindran, D., and Kumar, R. (2015), “An empirical study on service quality perceptions and continuance intention in mobile banking context in India”, *The Journal of Internet Banking and Commerce,* Vol.17 No.1, pp.76-84.

Richins, M. L. (1997), “Measuring emotions in the consumption experience”, *Journal of Consumer Research,* Vol. 24, pp. 127–146.

Reeves, B. and Nass, C. I. (1996), *The media equation: How people treat computers, television, and new media like real people and places*. Cambridge university press.

Roberts, R. J. and Weerts, T. C. (1982), “Cardiovascular responding during anger and fear imagery”, *Psychological Reports*, Vol. 50, pp. 219–230.

Robinson, S., Orsingher, C., Alkire, L., De Keyser, A., Giebelhausen, M., Papamichail, K., Shams, P. and Temerak, M. (2020). "Frontline encounters of the AI kind: An evolved service encounter framework”, *Journal of Business Research*, Vol. 116 No. C, pp. 366-376.

Robbins, S.P. and Judge, T.A. (2013), *Organisational behavior,* p. 686, 15th ed. Pearson Education.

Roseman, I. J. (1991), “Appraisal determinants of discrete emotions”, *Cognition & Emotion*, Vol. 5, pp. 161–200.

Roseman, I. J. (1996), “Appraisal determinants of emotions: constructing a more accurate and comprehensive theory”, *Cognition & Emotion*, Vol. 10, pp. 241–278.

Russell, J. A. (2003), “Core affect and the psychological construction of emotion”, *Psychological Review*, Vol. 110, pp. 145–172.

Ruth, J. A., Brunel, F. F. and Otner, C. C. (2002), "Linking thoughts to feelings: investigating cognitive appraisals and consumption emotions in a mixed-emotions context", *Journal of the Academy of Marketing Science*, Vol. 30, pp. 44–58.

Ruvalcaba-Romero, N.A., Fernández-Berrocal, P., Salazar-Estrada, J.G. and Gallegos-Guajardo, J. (2017), "Positive emotions, self-esteem, interpersonal relationships and social support as mediators between emotional intelligence and life satisfaction", *Journal Behavioral Health Soc. Issues*, Vol. 9, pp. 1–6.

Salovey, P. and Mayer, J.D. (1990), "Emotional intelligence", *Imagination, Cognition and Personality*, Vol. 9, pp.185–211.

Saviano, M., Parida, R., Caputo, F. and Kumar Datta, S. (2014), "Health care as a worldwide concern. Insights on the Italian and Indian health care systems and PPPs from a VSA perspective", *EuroMed Journal of Business*, Vol. 9 No. 2, pp. 198-220.

Schepers, J. and Wetzels, M. (2007), "A meta-analysis of the technology acceptance model: Investigating subjective norm and moderation effects", *Information & Management*, Vol. 44 No. 1, pp. 90–103.

Scherer, K. R. (2009a), "The dynamic architecture of emotion: Evidence for the component process model", *Cognition and Emotion*, Vol. 23 No. 7, pp. 1307-1351.

Scherer, A., Wünderlich,N. V., and Von Wangenheim, F . (2015), " The value of self-service: long-term effects of technology-based self-service usage on customer retention", *MIS Quarterly*, Vol. 39 No.1 (March 2015), pp. 177-200.

Scherer, K. R., and Moors, A. (2019), "The emotion process: event appraisal and component differentiation", *Annual Review of Psychology*, Vol. 70, pp. 719-745.

Schneider, B., and Bowen, D. E. (1999), "Understanding customer delight and outrage", *Sloan Management Review*, Vol. 41 No. 1, pp. 35-45.

Schwartz, G. E., Weinberger, D. A. and Singer, J. A. (1981), “Cardiovascular differentiation of happiness, sadness, anger, and fear following imagery and exercise”, *Psychosomatic Medicine*, Vol. 43, pp. 343–364.

Scott, M. L., Mende, M. and Bolton, L. E. (2013), “Judging the book by its cover? How consumers decode conspicuous consumption cues in buyer–seller relationships”, *Journal of Marketing Research*, Vol. 50 No. 3, pp. 334–347.

Sharma, N. and Patterson, P. G. (1999), “The impact of communication effectiveness and service quality on relationship commitment in consumer, professional services”, *Journal of Services Marketing*, Vol.13 No.2, pp. 151–170.

Sheppes, G., Scheibe, S., Suri, G., Radu, P., Blechert, J. and Gross, J.J. (2014), “Emotion regulation choice: a conceptual framework and supporting evidence”, *J Exp Psychol*, Vol. 143 No. 1, pp.163-81. doi: 10.1037/a0030831.

Shivhare, S.N. and Khethawat, S. (2012), “Emotion detection from Text”, *arXiv preprint arXiv:*1205.4944.

Skjuve, M., Haugstveit, I. M., Følstad, A. and Brandtzaeg, P. B. (2019), “Help! Is my Chatbot Falling into the Uncanny Valley? An Empirical Study of User Experience in Human-Chatbot Interaction”, *Human Technology*, Vol. 15 No. 1, pp. 30–54. ahref=https://doi.org/10.17011/ht/urn.201902201607 doi:10.17011/ht/urn.201902201607

Simon, F.L., and Usunier, J. (2007), “Cognitive, demographic, and situational determinants of service customer preference for personnel-in-contact over self-service technology”, *International Journal of Research in Marketing*, Vol. 24 No.2, pp. 163-173.

Singh, J., Brady, M., Arnold, T., and Brown, T. (2017), “The emergent field of organizational frontlines”, *Journal of Service Research*, Vol. 20 No. 1, pp. 3-11.

Sirianni, N.J., Bitner, M.J., Brown, S.W. and Mandel, N. (2013), “Branded Service Encounters: Strategically Aligning Employee Behavior with the Brand Positioning”, *Journal of Marketing*, Vol. 77, pp. 108–123.

Smith, C. A. and Ellsworth, P. C. (1985), “Patterns of cognitive appraisal in emotion”, *Journal of Personality and Social Psychology*, Vol. 48, pp. 813–838.

So, J., Achar, C., Han, D., Agrawal, N. and Duhachek, A. (2015), “The psychology of appraisal: specific emotions and decision-making”, *Journal of Consumer Psychology*, Vol. 25, pp. 359–371.

Söderlund, M. and Rosengren, S. (2008), “Revisiting the smiling service worker and customer satisfaction”, *International Journal of Service Industry Management*, Vol. 19 No. 5, pp. 552–574.

Solomon, M., Surprenant, C., Czepiel, J. and Gutman, E. (1985), “A role theory perspective on dyadic interactions: The service encounter”, *Journal of Marketing*, Vol. 49, pp. 99–111.

Srinivasan, S., Vanhuele, M. and Pauwels, K. (2010), “Mind-set metrics in market response models: an integrative approach”, *Journal of Marketing Research*, Vol. 47, pp. 672–684.

Stock, R.M. and Merkle, M. (2018), “Can humanoid service robots perform better than service employees? A comparison of innovative behavior cues”, *Proceedings of the 51st Hawaii International Conference on System Sciences, Waikoloa Village, HI, January 3-6*, available at: https://scholarspace.manoa.hawaii.edu/bitstream/10125/50020/1/paper0133.pdf (accessed February 3, 2018).

Subramony, M., Solnet, D., Groth, M., Yagil, D., Hartley, N., Beomcheol Kim, P. and Golubovskaya, M. (2018), "Service work in 2050: toward a work ecosystems perspective", *Journal of Service Management*, Vol. 29 No. 5, pp. 956-974.

Sutton, R.S. and Barto, A.G. (2000), *Reinforcement learning: an introduction*, The MIT Press Cambridge, Massachusetts, London, England.

Taillard, M., Peters, L. D., Pels, J., & Mele, C. (2016), “The role of shared intentions in the emergence of service ecosystems”, *Journal of Business Research*, Vol. 69 No. 8, pp. 2972-2980.

Tam, J.L.M. (2004), “Customer satisfaction, service quality and perceived value: An integrative model”, *Journal of Marketing Management*, Vol. 20, pp. 897–917.

Tamir, M. (2016), “Why do people regulate their emotions? A taxonomy of motives in emotion regulation”, *Personality and Social Psychology Review*, Vol. 20 No.3, pp. 199–222.

Tangney, J. P. and Dearing, R. L. (2002). *Shame and guilt*. New York, NY: Guil- ford Press.

Tax, S.S., McCutcheon, D. and Wilkinson, I.F. (2013), “The service delivery network (SDN) a customer-centric perspective of the customer journey”, *Journal of Service Research*, Vol. 16 No. 4, pp. 454-470.

Thurn, S. (2004), “Toward a framework for Human-Robot interaction”, *Human-Computer Interaction*, Vol. 19, pp. 9-24.

Tiedens, L. Z. and Linton, S. (2001), “Judgment under emotional certainty and uncertainty: the effects of specific emotions on information processing”, *Journal of Personality and Social Psychology*, Vol. 81, pp. 973–988.

Tinwell, A., Grimshaw, M. and Williams, A. (2011), “The uncanny wall”, *International Journal of Arts and Technology*, Vol. 4 No. 3, pp. 326-341.

Tronvoll, B., Barile, S. and Caputo, F. (2017), *A systems approach to understanding the philosophical foundation of marketing studies*. In Barile, S., Pellicano, M., Polese, F. (eds.) Social Dynamics in a System Perspective. Springer, New York.

Tsai, W. and Huang, Y. M. (2002), “Mechanisms linking employee affecting delivery and customer behavioral intentions”, *Journal of Applied Psychology*, Vol. 87, pp. 1001–1008.

Tsarenko, Y., and Tojib, D.R. (2011), “A transactional model of forgiveness in the service failure context: A customer-driven approach”, *Journal Services Marketing*, Vol. 25 No. 5, pp. 381–392.

Tung, V.W.S., and Law, R. (2017), “The potential for tourism and hospitality experience research in human-robot interactions”, *International Journal of Contemporary Hospitality Management*, Vol. 29, pp. 2498-2513.

Van Dijk, W. W. and Zeelenberg, M. (2002), “Investigating the appraisal patterns of regret and disappointment”, *Motivation and Emotion*, Vol. 26, pp. 321–331.

van Doorn, J., Mende, M., Nobble, S.M., Hulland, J., Ostrom, A.L., Grewal, D. and Petersen, J.A. (2017), "Domo Arigato Mr. Roboto: emergence of automated social presence in organizational frontlines and customers' service experiences", *Journal of Service Research*, Vol. 20 No. 1, pp. 43-58.

van Pinxteren, M., Wetzels, R., Rüger, J. and Wetzels, M. (2019), "Trust in humanoid robots: Implications for services marketing", *Journal of Services Marketing*, Vol. 33 No. 4, pp. 507–518.

Vargo, S. L., and Lusch, R. F. (2004), "Evolving to a new dominant logic for marketing", *Journal of Marketing*, Vol. 68 No. 1, pp. 1-17.

Vargo, S. L., and Lusch, R. F. (2008), "Service-dominant logic: continuing the evolution", *Journal of the Academy of Marketing Science*, Vol. 36 No. 1, pp. 1-10.

Vargo, S. L., and Lusch, R. F. (2011), "It's all B2B and beyond…: Toward a systems perspective of the market", *Industrial Marketing Management*, Vol. 40 No. 2, pp. 181-187.

Vargo, S. L., and Lusch, R. F. (2016), "Istitutions and axioms: An extension and update of service dominant logic", *Journal of the Academy of Marketing Science*, Vol. 44 No. 1, pp. 5-23.

Vargo, S. L., and Lusch, R. F. (2017), "Service dominant logic 2025", *International Journal of Research in Marketing*, Vol. 34 No. 1, pp. 46-67.

Vargo, S.L., Maglio, P.P. and Akaka, M.A. (2008), "On value and value co-creation: A service systems and service logic perspective", *European Management Journal*, Vol. 6 No. 3, pp.154-152.

Vargo, S. L. and Lusch, R. F. (2008a), "From goods to service (s): Divergences and convergences of logics", *Industrial marketing management*, Vol. 37 No. 3, pp. 254-259.

Vargo, S. L. and Lusch, R. F. (2008b), "Service-dominant logic: continuing the evolution", *Journal of the Academy of marketing Science*, Vol. 36 No. 1, pp. 1-10.

Vaussard, F.C., Fink, J., Bauwens, V., Rétornaz, P., Hamel, D., Dillenbourgh, P., and Mondada, F. (2014), "Lesson Learned from Robotic Vacuum Cleaners Entering in the Home Ecosystem", *Robotics and Autonomous Systems*, Vol. 62, pp. 376-391.

Venkatesh, V. and Davis, F.D. (2000), "A theoretical extension of the technology acceptance model: our longitudinal field studies", *Management science*, Vol. 46, pp. 186-204.

Venkatesh, V., Thong, J. and Xu, X. (2012), "Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology", *MIS Quarterly*, Vol. 36 No. 1, pp. 157–178.

Venkatesh, V., Morris, M., Davis, G. and Davis, F. (2003), "User acceptance of information technology: Toward a unified view", *MIS Quarterly*, Vol. 27 No. 3, pp. 425–478.

Venkatesh, V., and Bala, H. (2008), "Technology acceptance model 3 and research agenda on interventions", *Decision Science*, Vol. 39, pp. 273-315.

Verhoef, P. C., Kannan, P. K. and Inman, J. J. (2015), "From multi-channel retailing to omni-channel retailing: introduction to the special issue on multi-channel retailing", *Journal of Retailing*, Vol. 91 No. 2, pp. 174–181.

Wang, R. J. H., Malthouse, E. C. and Krishnamurthi, L. (2015), "On the Go: How Mobile Shopping Affects Customer Purchase Behavior", *Journal of Retailing*, Vol. 91 No. 2, pp. 217-234. https://doi.org/10.1016/j.jretai.2015.01.002

Wang, Y. and Petrina, S. (2013), "Using learning analytics to understand the design of an intelligent language tutor", *International Journal of Advanced Computer Science & Applications,* Vol. 4 No. 11, pp. 124-131.

Watson, G., Beck, J., Henderson, C. and Palmatier, R. (2015), "Building, measuring, and profiting from customer loyalty", *Journal of the Academy of Marketing Science*, Vol. 43, pp. 790–825.

Webster, C., and Sundaram, D. S. (2009), "Effect of service provider's communication style on customer satisfaction in professional services setting: The moderating role of criticality and service nature", *Journal of Services Marketing*, Vol. 23 No. 2, pp. 103–113.

Wieland, H., Hartman, N., & Vargo, S. L. (2017), "Business models as service strategy", *Journal of the Academy of Marketing Science*, available at: https://link.springer.com/article/10.1007/s11747-017-0531-z

Wieseke, J., Geigenmüller, A. and Kraus, F. (2012), "On the Role of Empathy in Customer-Employee Interactions", *Journal of Service Research*, Vol. 15 No. 3, pp. 316–331.

Wilder, K. M., Collier, J. E. and Barnes, D. C. (2014), "Tailoring to customers' needs: Understanding how to promote an adaptive service experience with frontline employees", *Journal of Service Research*, Vol. 17 No. 4, pp. 446-459.

Wirtz, J., Patterson, P. G., Kunz, W. H., Gruber, T., Lu, V. N., Paluch, S., and Martins, A. (2018), "Brave new world: service robots in the frontline", *Journal of Service Management*, Vol. 29 No. 5, pp. 907-931.

Yih, J., Uusberg, A., Taxer, J. L. and Gross, J. J. (2019), "Better together: a unified perspective on appraisal and emotion regulation", *Cognition and Emotion*, Vol. 33, pp. 1–7.

Zaki, J. and Ochsner, K., (2016), *Empathy*, in Feldman-Barrett, L., Lewis, M., and Haviland-Jones, J.M. (Eds), Handbook of Emotions, pp. 871-884, The Guilford Press, New York.

Zeelenberg, M., Nelissen, R. M. A., Breugelmans, S. M. and Pieters, R. (2008), "On emotion specificity in decision making: why feeling is for doing", *Judgment and Decision making*, Vol. 3, pp. 18–27.

Zeithaml, V. A., Berry, L. L., and Parasuraman, A. (1996), "The behavioral consequences of service quality", *Journal of Marketing*, Vol. 60 No. 2, pp. 31-46.

APPENDICES

APPENDIX 01: Self-administered Questionnaire

Chatbots: the impact of emotional awareness on customer acceptance

1. Aim of the study

The study aims to examine how the emotional capacity of conversational agents affects their acceptance by users. Conversational agents or chatbots are artificial intelligence tools that are used by the main customer care channels. They are virtual operators who respond via chat instead of human operators to the first customer requests. Often, they are also used through Facebook messenger directly from company pages.
The survey has up to 26 questions, and should take 8 minutes to complete.
Once you submit the survey, you are unable to edit your answers.
The survey is anonymous and your answers are for research and non-commercial purposes.
If you have any questions about this survey, please contact the researcher Marzia Del Prete.

2. Interaction with a chatbot

* 1. Dear participant, did you already interact with a chatbot in the past?
◊ Yes
◊ No

3. Screener

* 2. The study requires that you read questions carefully. We use multiple checks to see if you are reading the questions attentively. Responding to questions incorrectly will result in the termination of the study. We greatly appreciate your time and participation!

◊ I realize that this survey requires careful attention and I am willing to do that at this time

◊ I cannot participate in a survey that requires paying careful attention to questions at this time

* 3. Which of the following words is MOST related to "moody"?

◊ distant

◊ stable

◊ fantastic

◊ emotional

* 4. Which of the following words is MOST related to "happy"?

◊ thoughtful

◊ unfocused

◊ generous

◊ joyful

* 5. Which of the following words is MOST closely related to "guilty"?

◊ culpable

◊ tame

◊ forgetful

◊ lucky

* 6. Which of the following words is MOST closely related to "empathy"?

◊ compassion

◊ sociable

◊ truthful

◊ honest

4. Main Study

* 7. In which customer care context did you use the chatbot?

◊ To request information on a product or service

◊ To request technical assistance on a product or service

◊ To make a complaint about a product or service

◊ To purchase a product or service

◊ Other (Specify)

* 8. In which industry have you used the chatbot?

◊ Telecommunications

◊ Banking

◊ Retail

◊ Health care and social assistance

◊ Utilities

◊ Computer and electronics Manufacturing

◊ Hotel and Food Services

◊ Finance and Insurance

◊ Arts, Entertainment, and Recreation

◊ Transportation and Warehousing

◊ Scientific or Technical Services

◊ Construction

◊ Publishing

◊ Wholesale

◊ Other (Specify)

5. Functional Elements

* 9. Instructions: Here are a number of characteristics that may or may not apply to you. Please select your answer next to each statement to indicate the extent to which you agree or disagree with that statement.

	Strongly Disagree	Disagree	Somewhat Disagree	Neither Agree nor Disagree	Somewhat Agree	Agree	Strongly Agree
I find chatbots easy to use	○	○	○	○	○	○	○
I think I can use chatbots without any help	○	○	○	○	○	○	○
I think chatbots can help me for almost all my needs	○	○	○	○	○	○	○
People who influence me think I should use chatbots	○	○	○	○	○	○	○
People important to me think I should use chatbots	○	○	○	○	○	○	○

6. Social Elements

* 10. Instructions: Here are a number of characteristics that may or may not apply to you. Please select your answer next to each statement to indicate the extent to which you agree or disagree with that statement.

	Strongly Disagree	Disagree	Somewhat Disagree	Neither Agree nor Disagree	Somewhat Agree	Agree	Strongly Agree
Sometimes the chatbot seems to have real feelings	○	○	○	○	○	○	○
I can imagine the chatbot to be a person	○	○	○	○	○	○	○
I find the chatbot pleasant to interact with	○	○	○	○	○	○	○
I feel the chatbot understand me	○	○	○	○	○	○	○
If you read the characteristics correctly, select agree	○	○	○	○	○	○	○
When I interact with a chatbot, I feel to talk with a real person	○	○	○	○	○	○	○
I often think the chatbot is a real person	○	○	○	○	○	○	○

7. Relational Elements

* 11. Instructions: Here are a number of characteristics that may or may not apply to you. Please select your answer next to each statement to indicate the extent to which you agree or disagree with that statement.

	Strongly Disagree	Disagree	Somewhat Disagree	Neither Agree nor Disagree	Somewhat Agree	Agree	Strongly Agree
I feel I can rely on the chatbot for my needs	○	○	○	○	○	○	○
I believe the chatbot provide accurate information	○	○	○	○	○	○	○
The chatbot relates well to me	○	○	○	○	○	○	○
If you read the characteristics correctly, select agree	○	○	○	○	○	○	○
I believe there is an emotional connection between the chatbot and me	○	○	○	○	○	○	○

8. Technology Literacy

* 12. Instructions: Here are a number of two characteristics that may or may not apply to you. Please select your answer next to each statement to indicate the extent to which you agree or disagree with that statement.

	Strongly Disagree	Disagree	Somewhat disagree	Neither Agree nor Disagree	Somewhat Agree	Agree	Strongly Agree
I believe that my knowledge of the new technologies facilitates my use of the chatbot.	○	○	○	○	○	○	○
I think less experienced people might have difficulty using the chatbots.	○	○	○	○	○	○	○

9. Emotional Awareness

* 13. Instructions: Here are a number of three characteristics that may or may not apply to you. Please select your answer next to each statement to indicate the extent to which you agree or disagree with that statement.

	Strongly Disagree	Disagree	Somewhat Disagree	Neither Agree nor Disagree	Somewhat Agree	Agree	Strongly Agree
The chatbot seemed to know how I was feeling	○	○	○	○	○	○	○
The chatbot seemed to understand me	○	○	○	○	○	○	○
If you read the characteristics correctly, select agree	○	○	○	○	○	○	○
The chatbot put itself in my shoes	○	○	○	○	○	○	○

10. Negative Emotions

* 14. Instructions: Here are a number of two characteristics that may or may not apply to you. Please select your answer next to each statement to indicate the extent to which you agree or disagree with that statement.

	Strongly Disagree	Disagree	Somewhat disagree	Neither Agree nor Disagree	Somewhat Agree	Agree	Strongly Agree
I think the chatbot is able to recognize my guilt when I am unable to make a purchase	○	○	○	○	○	○	○
The chatbot diverted me to a human operator when it recognized my guilt	○	○	○	○	○	○	○

11. Positive Emotion

* 15. Instructions: Here are a number of characteristics that may or may not apply to you. Please select your answer next to each statement to indicate the extent to which you agree or disagree with that statement.

	Strongly Disagree	Disagree	Somewhat Disagree	Neither Agree nor Disagree	Somewhat Agree	Agree	Strongly Agree
I think the chatbot recognizes my happiness	○	○	○	○	○	○	○
If you read the characteristics correctly, select agree	○	○	○	○	○	○	○
I think the chatbot is able to give me a pleasant experience and motivate me if it recognizes my happiness	○	○	○	○	○	○	○

12. Customer Acceptance of chatbots

* 15. Instructions: Here are a number of three characteristics that may or may not apply to you. Please select your answer next to each statement to indicate the extent to which you agree or disagree with that statement.

	Strongly Disagree	Disagree	Somewhat disagree	Neither Agree nor Disagree	Somewhat Agree	Agree	Strongly Agree
I will try to use the chatbot in the future	○	○	○	○	○	○	○
I plan to use the chatbot in the future	○	○	○	○	○	○	○
I intend to use the chatbot in the future	○	○	○	○	○	○	○

13. Demographic Questions

* 17. What is your gender?

◊ Male

◊ Female

◊ Other

* 18. What is your year of birth?

* 19. What is the highest level of school you have completed or the highest degree you have received?

◊ High school graduate - high school diploma or equivalent (for example: GED)

◊ Bachelor's degree (For example: BA, AB, BS)

◊ Master's degree (For example: MA, MS, MEng, MEd, MSW, MBA)

◊ Professional School Degree (For example: MD,DDS,DVM,LLB,JD)

◊ Doctorate degree (For example: PhD, EdD)

◊ Other

20. Which of the following best describe your role in industry?

◊ Upper Management

◊ Middle Management

◊ Junior Management

◊ Administrative Staff

◊ Support Staff

◊ Student

◊ Trained Professional

◊ Skilled Laborer

◊ Consultant

◊ Temporary Employee

◊ Researcher

◊ Self-employed/Partner

Other (Specify)

14. Technical questions

* 21. What browser are you currently taking this survey on?

◊ Google Chrome

◊ Internet Explorer

◊ Firefox

◊ Safari

◊ Other (Specify)

* 22. How often do you participate in online surveys?

◊ A few times per year

◊ A few times per month

◊ A few times per week

◊ More than ten time per week

* 23. Why do you participate in online surveys?

◊ To kill time

◊ To make money

◊ To have fun

◊ I enjoy doing interesting tasks

◊ To gain self-knowledge

◊ To earn rewards (e.g., shopping rewards)

◊ Other (please specify)

15. Your opinion about our survey

24. Is there anything else you want to tell us? Any feedback about this study would be greatly appreciated! (If you experienced any technical difficulties while taking this study please let us know).
Attention: The way you answer this question will not, in any way, affect the payment you receive, and you will be paid in full no matter your response after that your survey is accepted by the researcher.

* 25. For the purposes of this research, it is very important that we only use responses that are thoughtful and honest. If there is any reason, we should not include your data (or part of your data) in our analysis, please indicate so below:

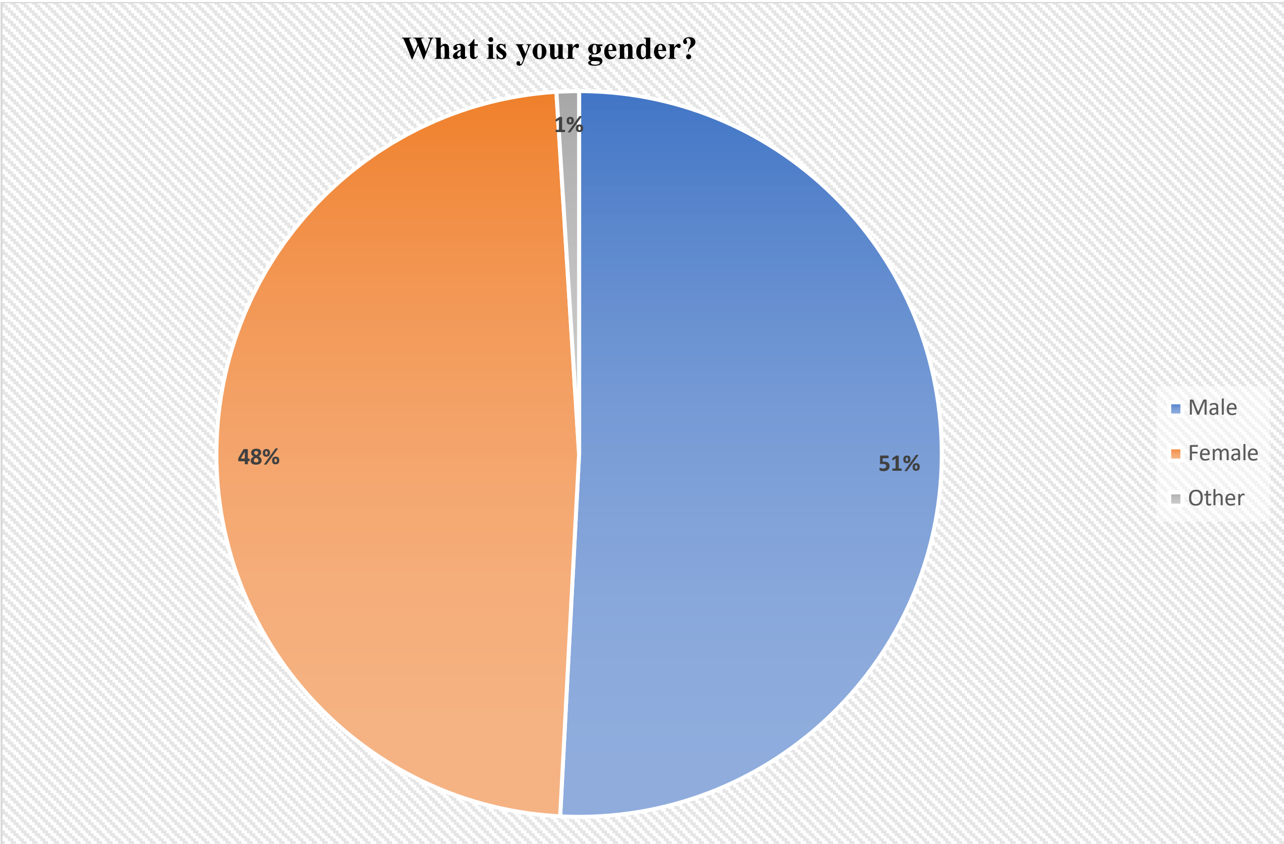
◊ Use my data in your analysis
◊ It would be better for you to not use my data in your analysis

* 26. Enter the following code as a completion code in the MTurk

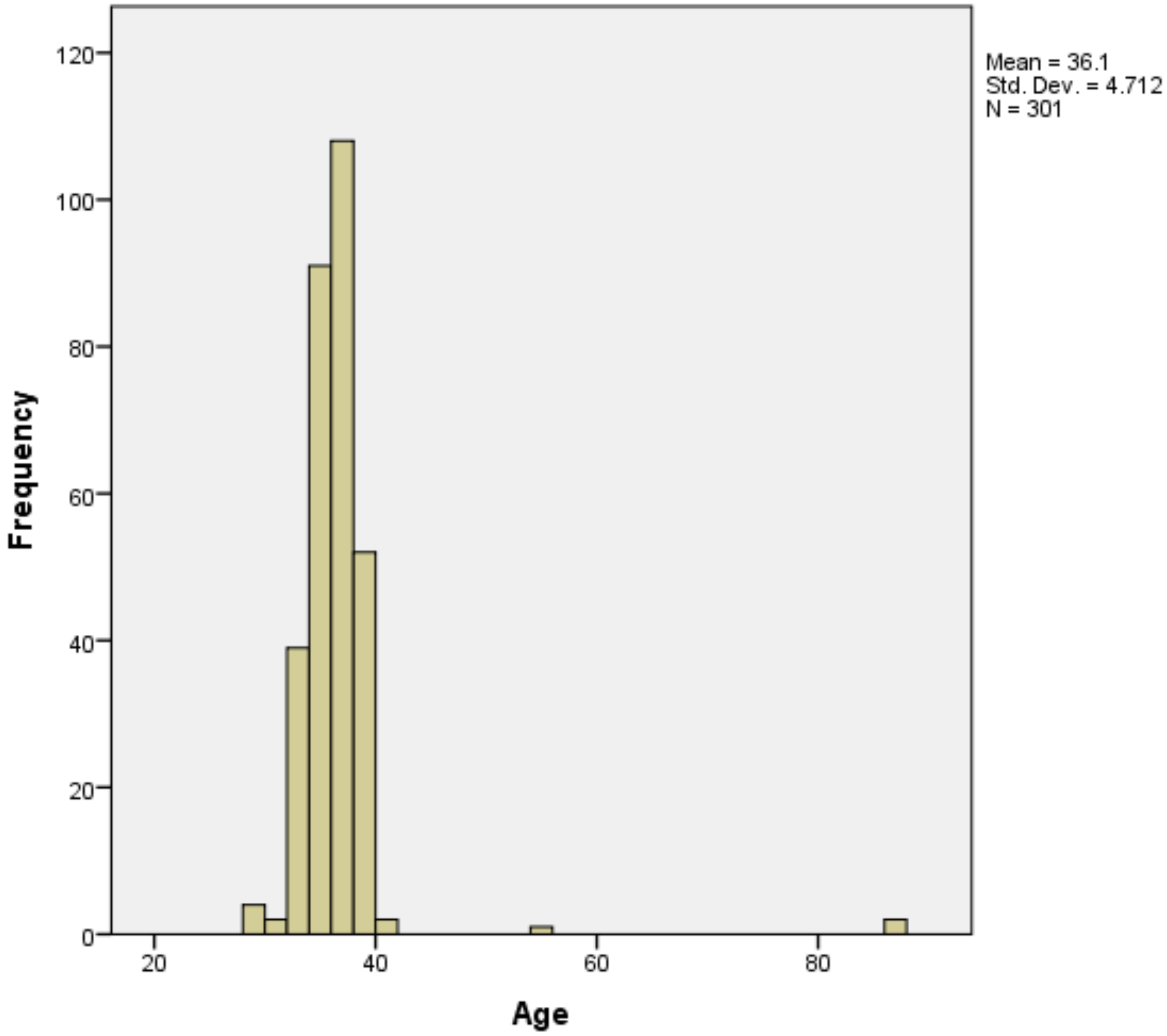
◊ Yes, I have entered the code on MTurk

APPENDIX 02: Data Analysis

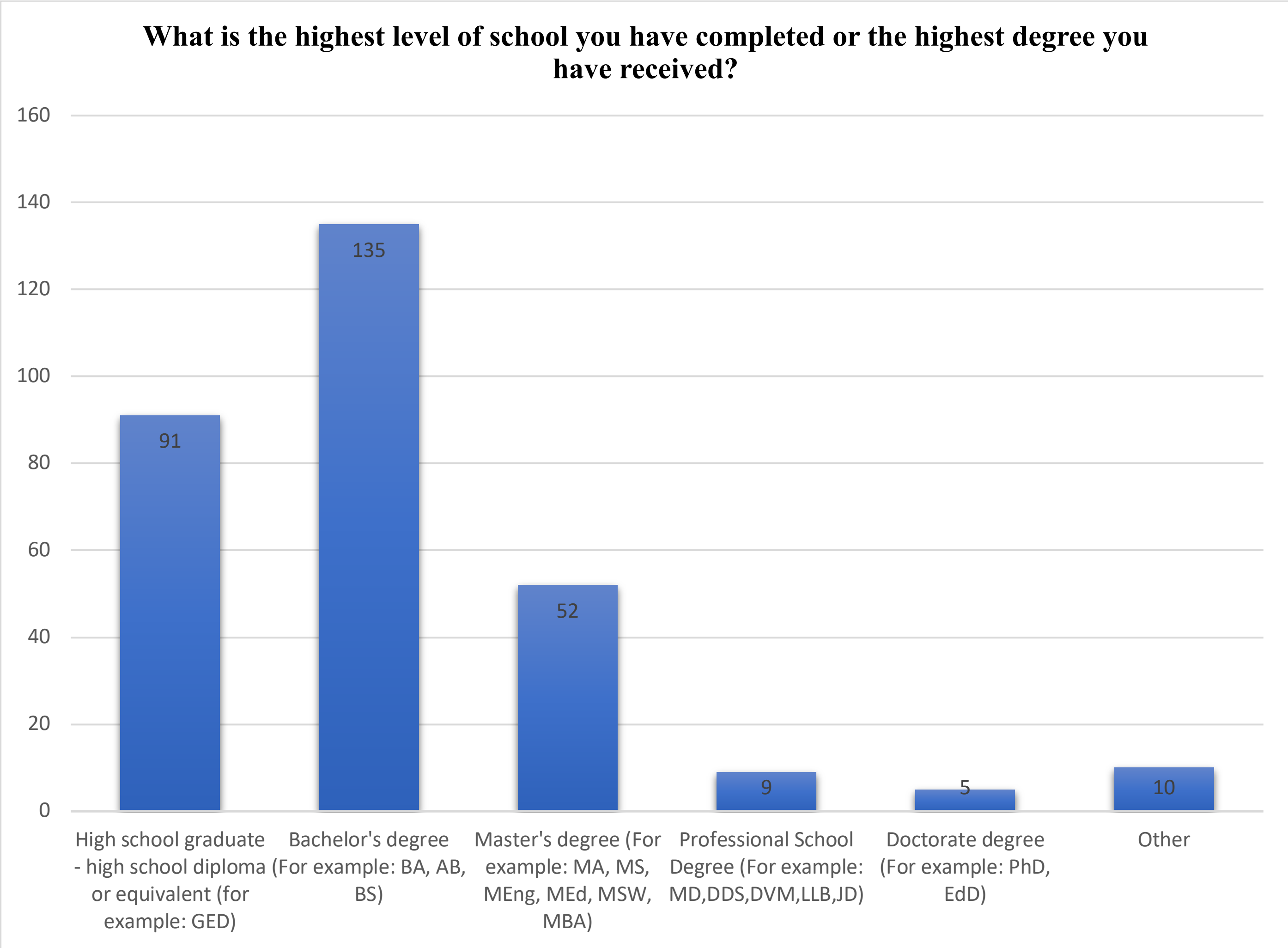
Respondents' Gender



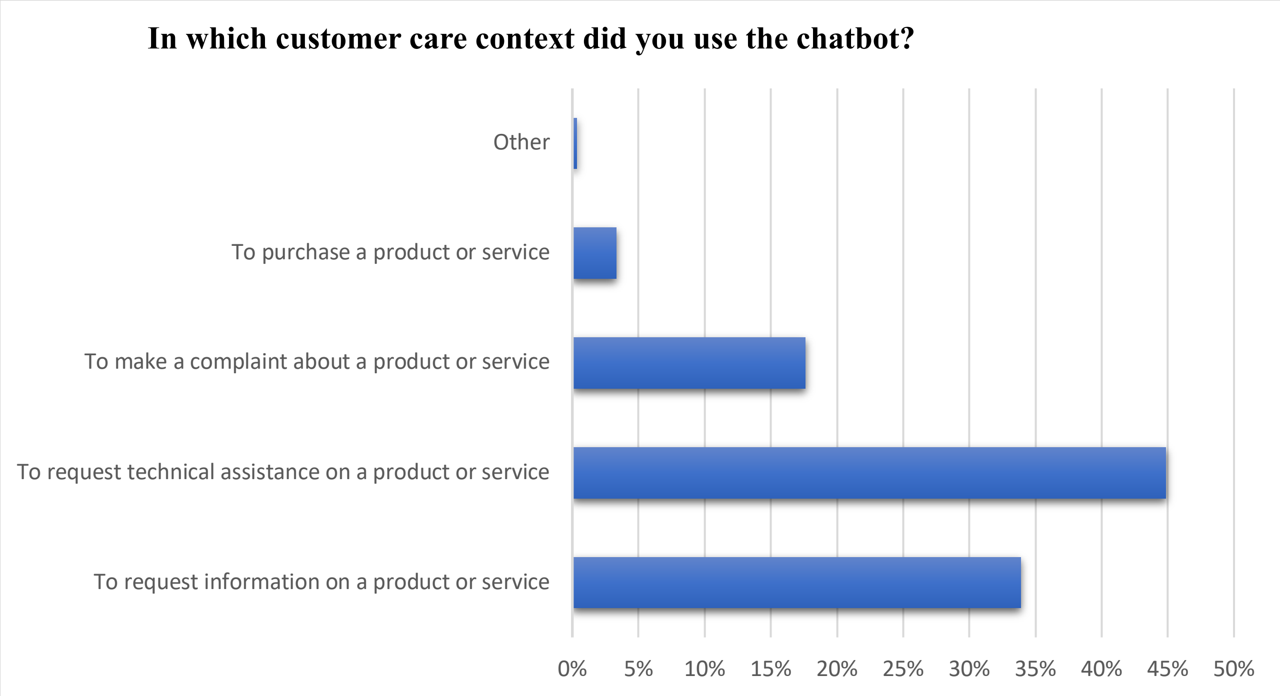
Respondents' age distribution



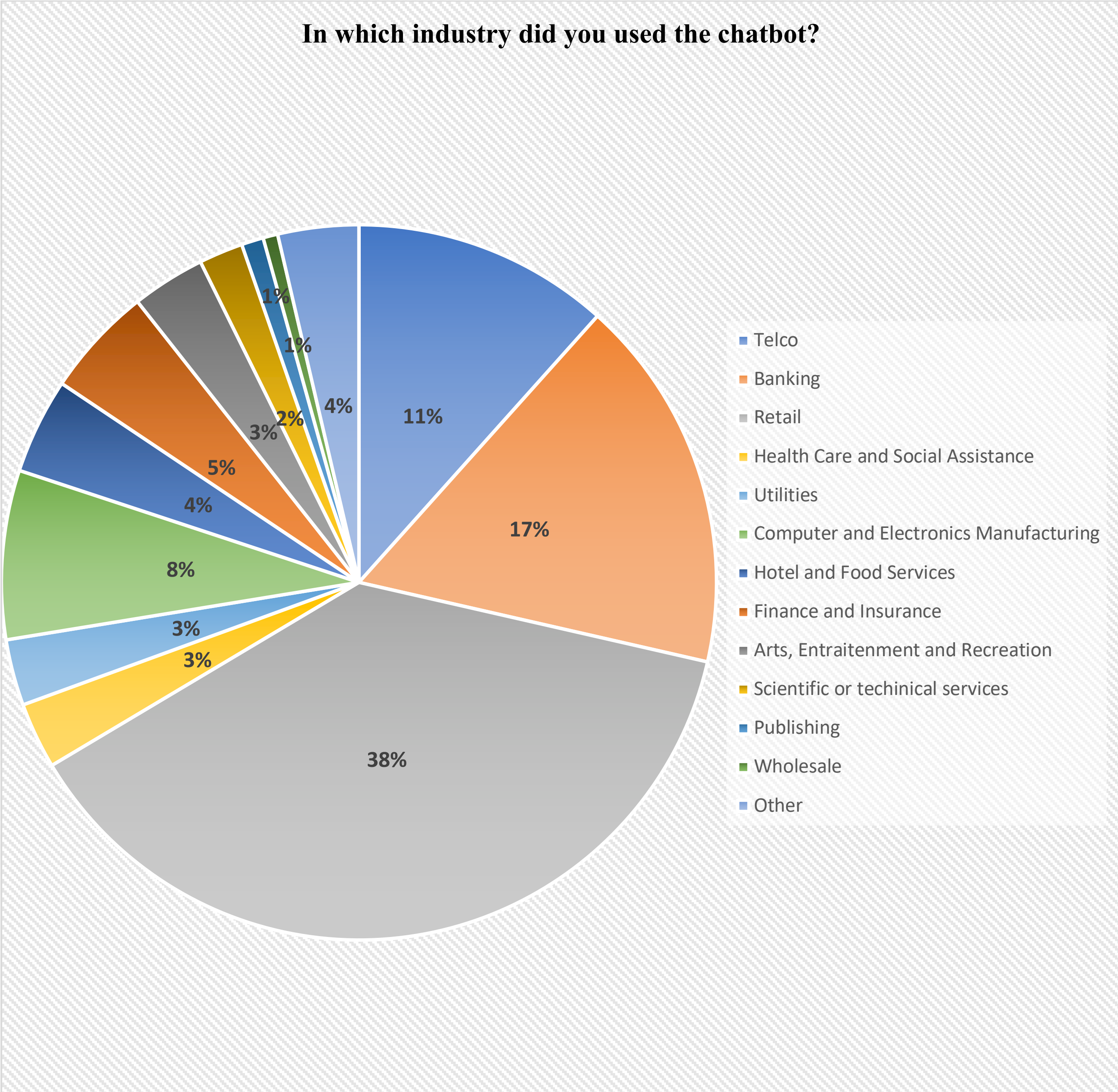
Respondents' Level of Education



Customer care context in which respondents use the chatbot



Industry in which respondents used the chatbot

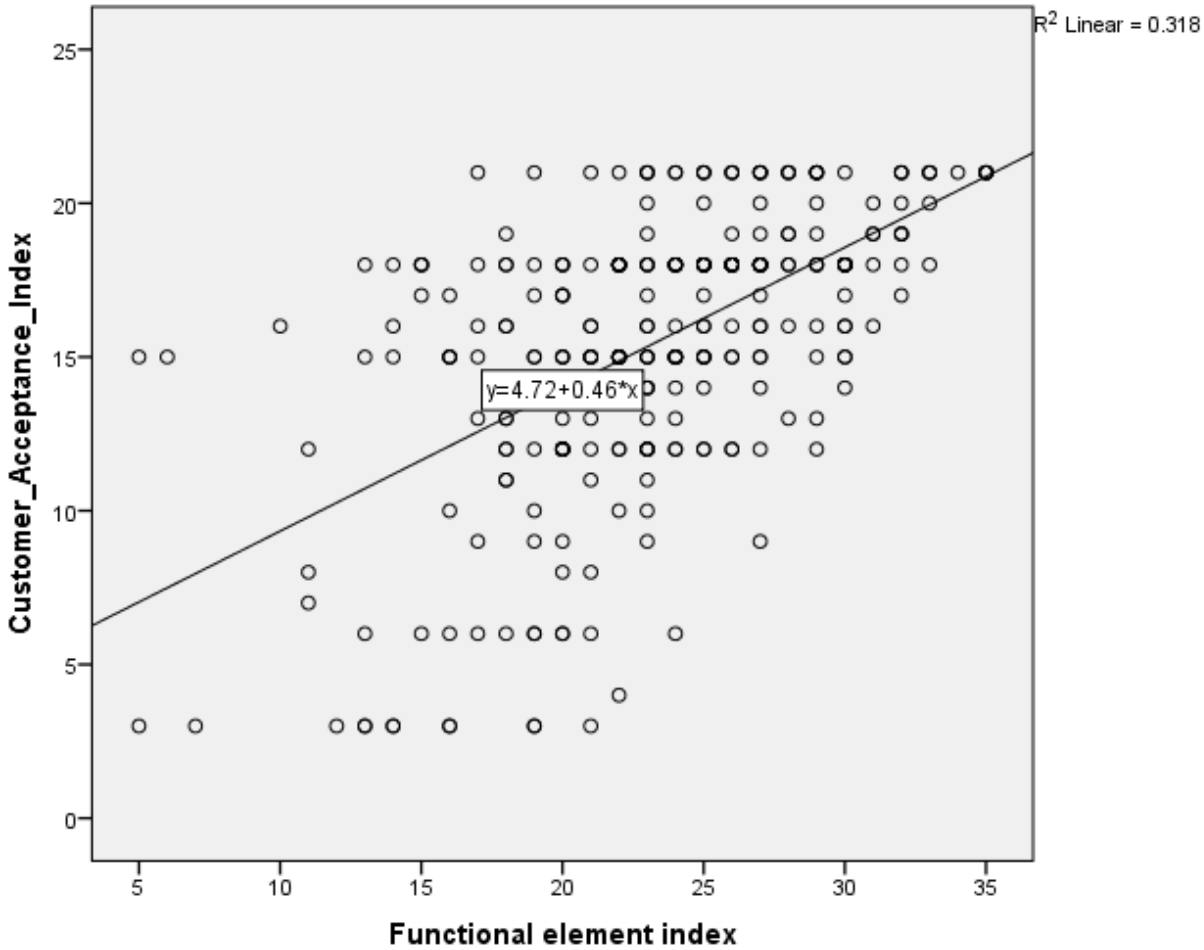


Direct effects

Functional elements

Regarding **H1**:

Scatter Plot of Functional Element Index and Customer Acceptance Index.



ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1941.555	1	1941.555	139.695	.000[b]
	Residual	4155.674	299	13.899		
	Total	6097.229	300			

a. Dependent Variable: Customer_Acceptance_Index

b. Predictors: (Constant), Functional element index

Coefficients[a]

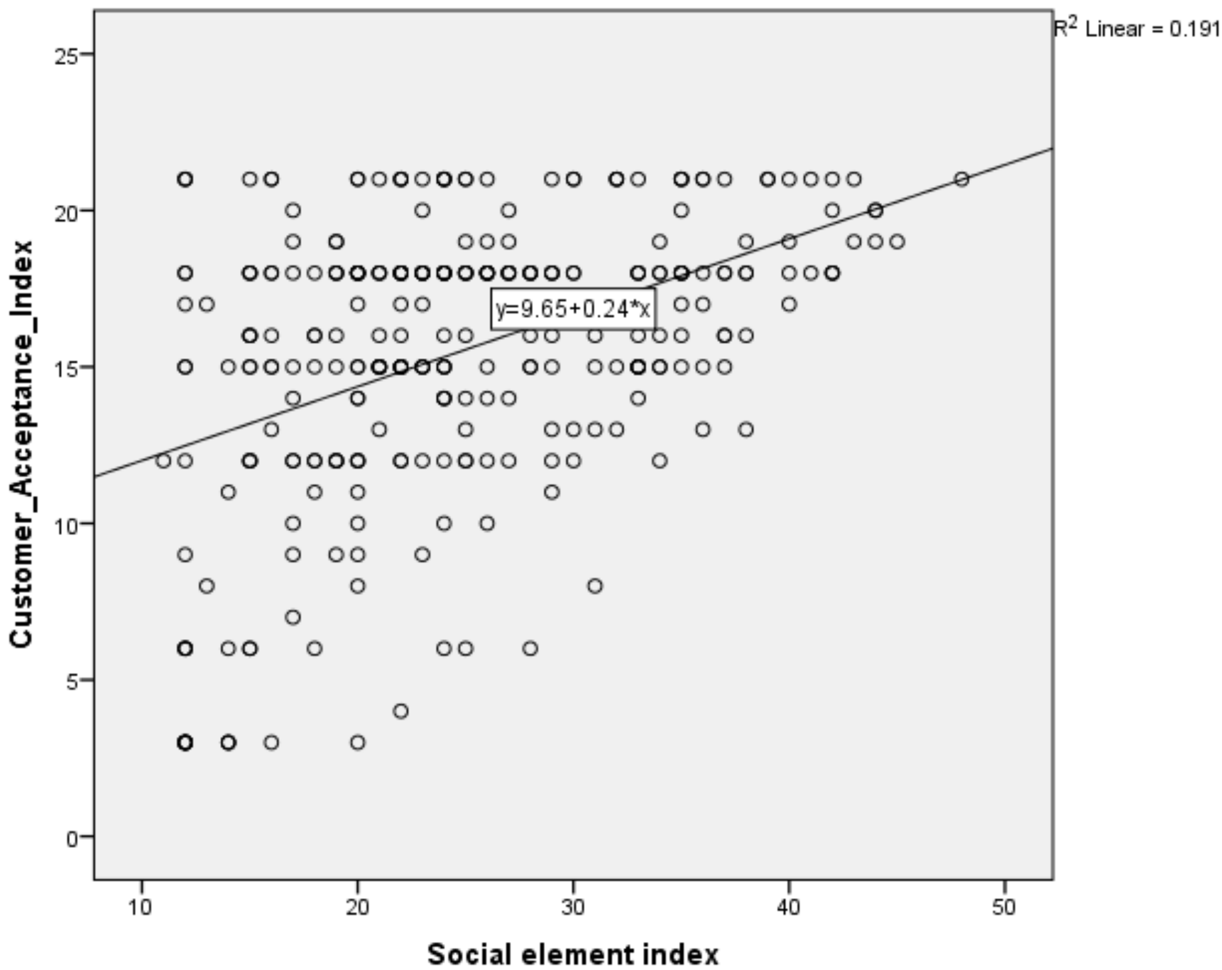
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	4.724	.937		5.040	.000
	Functional element index	.461	.039	.564	11.819	.000

a. Dependent Variable: Customer_Acceptance_Index

Social elements

Regarding **H2**:

Scatter Plot of Social Element Index and Customer Acceptance Index.



ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1164.931	1	1164.931	70.619	.000[b]
	Residual	4932.298	299	16.496		
	Total	6097.229	300			

a. Dependent Variable: Customer_Acceptance_Index

b. Predictors: (Constant), Social element index

Coefficients[a]

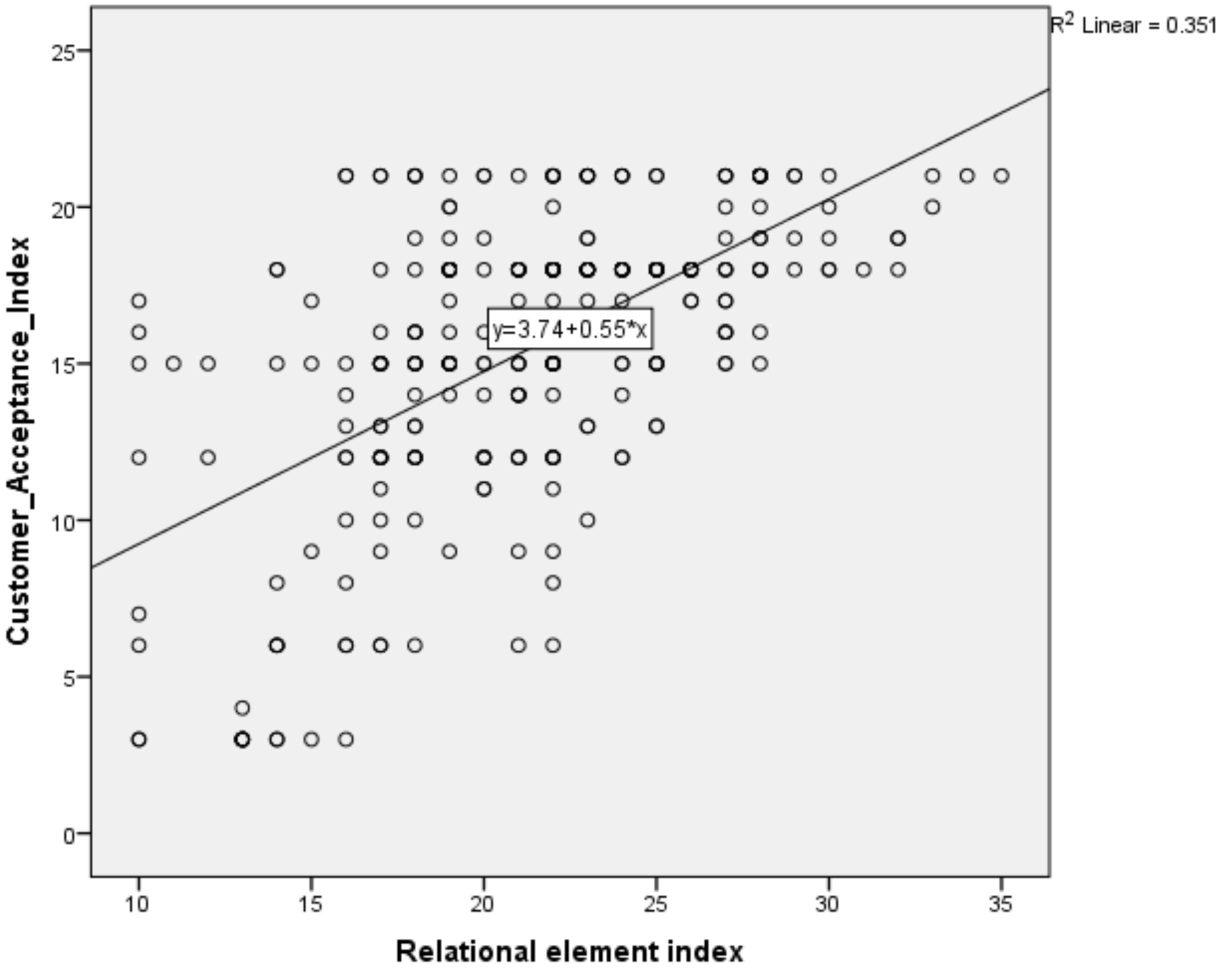
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	9.649	.735		13.120	.000
	Social element index	.236	.028	.437	8.404	.000

a. Dependent Variable: Customer_Acceptance_Index

Relational Elements

Regarding **H3**:

Scatter Plot of Relational Element Index and Customer Acceptance Index.



ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	2138.376	1	2138.376	161.505	.000[b]
	Residual	3958.853	299	13.240		
	Total	6097.229	300			

a. Dependent Variable: Customer_Acceptance_Index

b. Predictors: (Constant), Relational element index

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	3.738	.950		3.937	.000
	Relational element index	.551	.043	.592	12.708	.000

a. Dependent Variable: Customer_Acceptance_Index

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	2423.836	3	807.945	65.324	.000[b]
	Residual	3673.393	297	12.368		
	Total	6097.229	300			

a. Dependent Variable: Customer_Acceptance_Index

b. Predictors: (Constant), Relational element index, Functional element index, Social element index

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	2.053	.986		2.081	.038
	Functional element index	.242	.051	.296	4.739	.000
	Social element index	-.027	.039	-.050	-.697	.487
	Relational element index	.396	.078	.426	5.074	.000

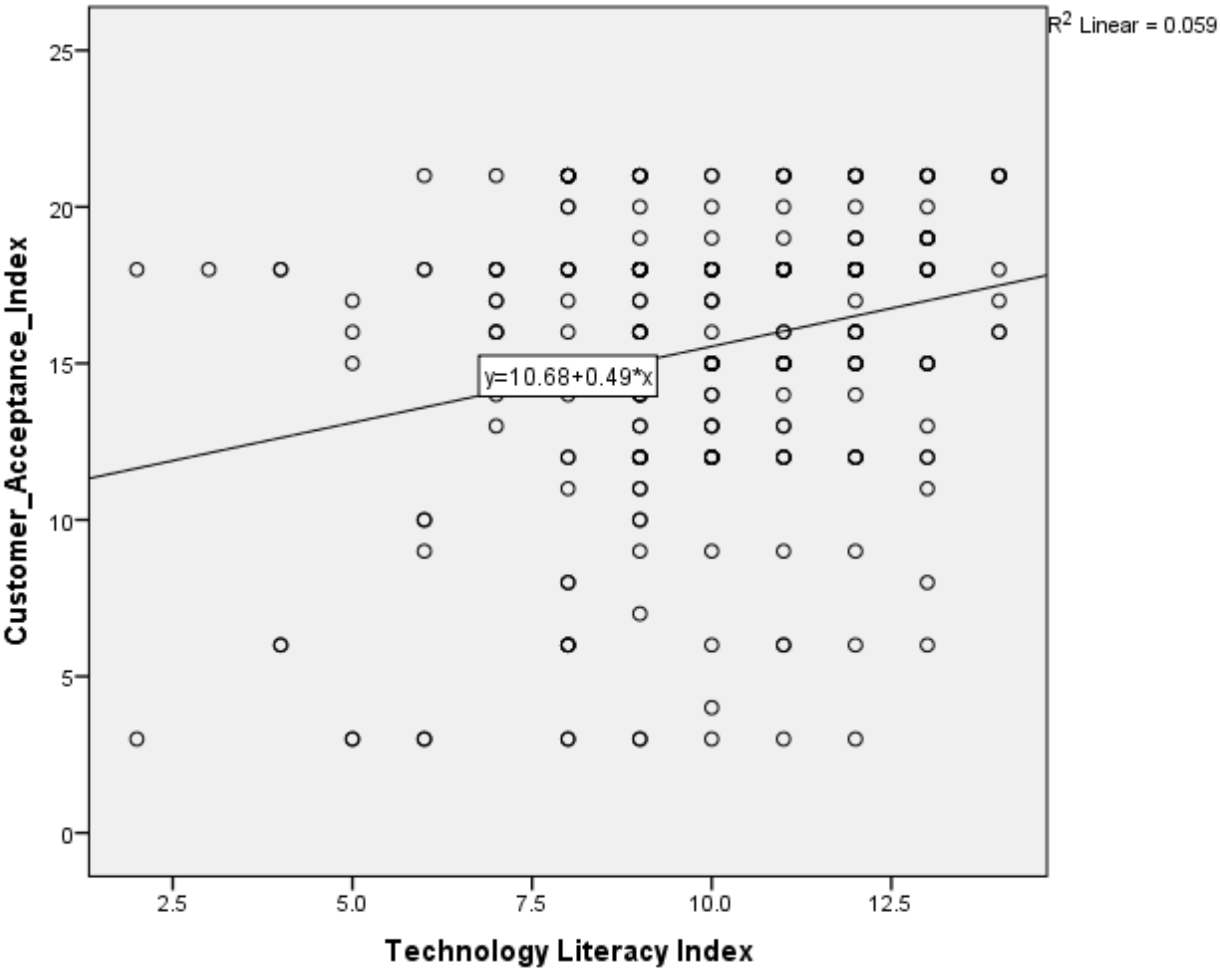
a. Dependent Variable: Customer_Acceptance_Index

Moderator effects

Technology Literacy

Regarding **H4**:

Scatter Plot of Technology Literacy Index and Customer Acceptance Index.



ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	360.848	1	360.848	18.809	.000[b]
	Residual	5736.381	299	19.185		
	Total	6097.229	300			

a. Dependent Variable: Customer_Acceptance_Index

b. Predictors: (Constant), Technology Literacy Index

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	10.675	1.143		9.343	.000
	Technology Literacy Index	.487	.112	.243	4.337	.000

a. Dependent Variable: Customer_Acceptance_Index

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	20.198	1.429		14.139	.000
	Technology Literacy index	.320	.140	.131	2.280	.023

a. Dependent Variable: Functional element index

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	40.627	3	13.542	2.714	.045[b]
	Residual	1481.765	297	4.989		
	Total	1522.392	300			

a. Dependent Variable: Technology Literacy Index

b. Predictors: (Constant), Relational element index, Functional element index, Social element index

Coefficients[a]

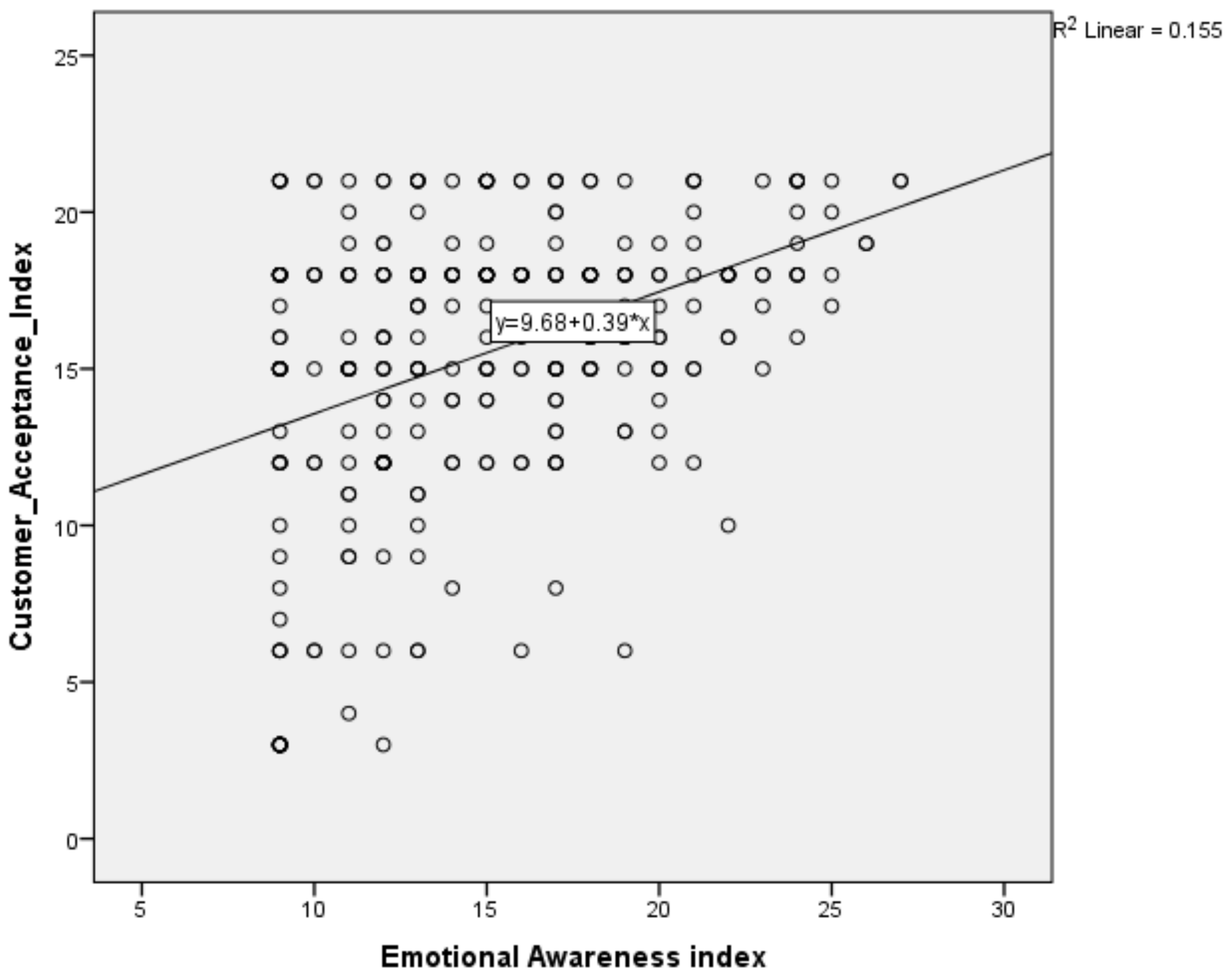
Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	8.240	.627		13.152	.000
	Functional element index	.024	.032	.058	.734	.464
	Social element index	-.028	.025	-.102	-1.122	.263
	Relational element index	.085	.050	.183	1.710	.088

a. Dependent Variable: Technology Literacy Index

Emotional Awareness

Regarding **H5:**

Scatter Plot of Emotional Awareness Index and Customer Acceptance Index.



ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	945.466	1	945.466	54.873	.000[b]
	Residual	5151.763	299	17.230		
	Total	6097.229	300			

a. Dependent Variable: Customer_Acceptance_Index

b. Predictors: (Constant), Emotional Awareness index

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	T	Sig.
		B	Std. Error	Beta		
1	(Constant)	9.682	.822		11.777	.000
	Emotional Awareness index	.389	.052	.394	7.408	.000

a. Dependent Variable: Customer_Acceptance_Index

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-2.219	.435		-5.096	.000
	Emotional Awareness index	.554	.028	.755	19.919	.000

a. Dependent Variable: Relational element index

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	4370.773	3	1456.924	229.531	.000[b]
	Residual	1885.174	297	6.347		
	Total	6255.947	300			

a. Dependent Variable: Emotional Awareness index

b. Predictors: (Constant), Relational element index, Functional element index, Social element index

Coefficients[a]

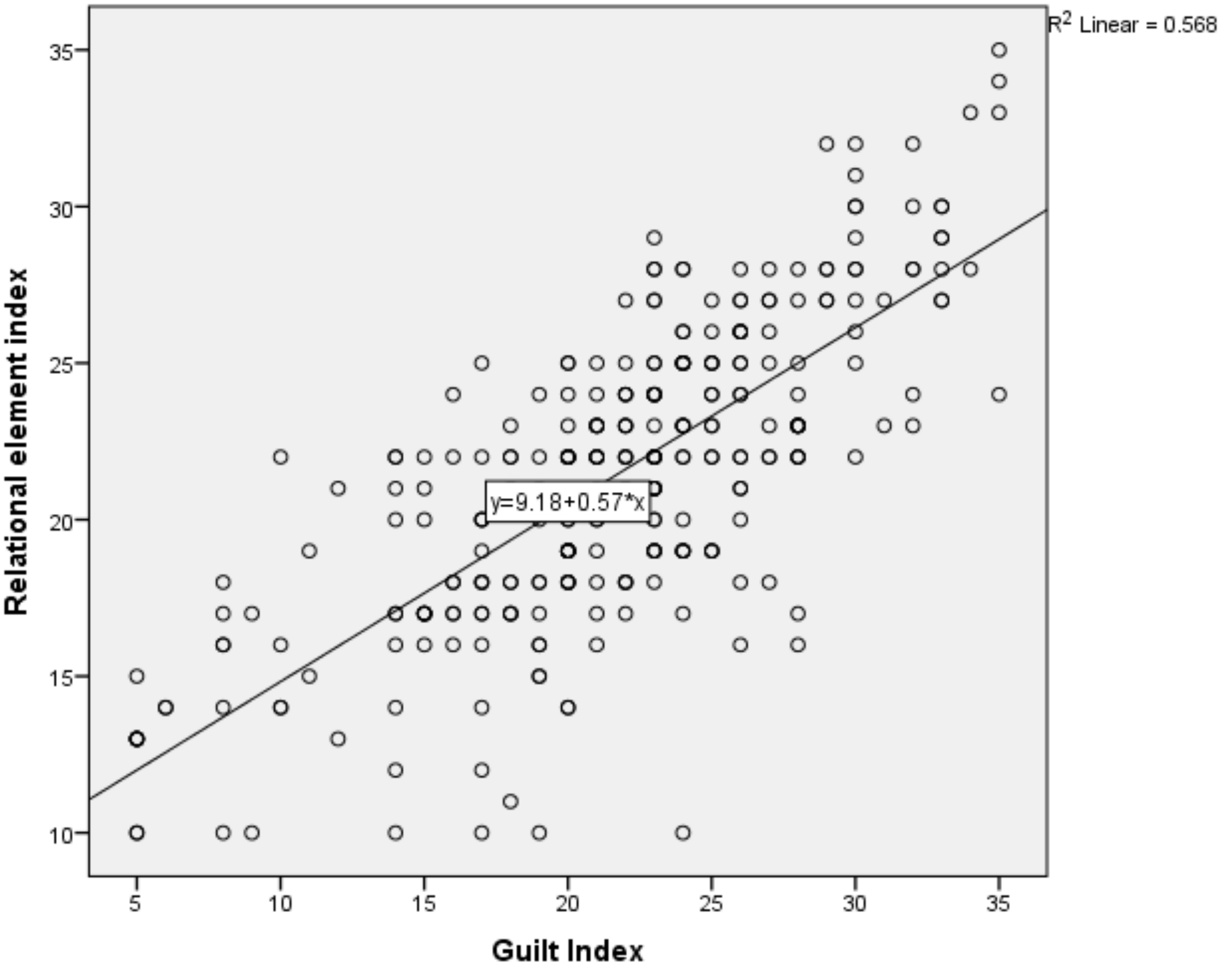
Model		Unstandardized Coefficients		Standardized Coefficients	T	Sig.
		B	Std. Error	Beta		
1	(Constant)	1.418	.707		2.007	.046
	Functional element index	.007	.037	.009	.199	.842
	Social element index	.345	.028	.630	12.464	.000
	Relational element index	.227	.056	.241	4.056	.000

a. Dependent Variable: Emotional Awareness index

Emotions of Guilt and Happiness

Regarding **H6 –Guilt:**

Scatter Plot if Guilt Index and Relational Element Index.



ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	4010.104	1	4010.104	393.803	.000[b]
	Residual	3044.720	299	10.183		
	Total	7054.824	300			

a. Dependent Variable: Relational element index

b. Predictors: (Constant), Guilt Index

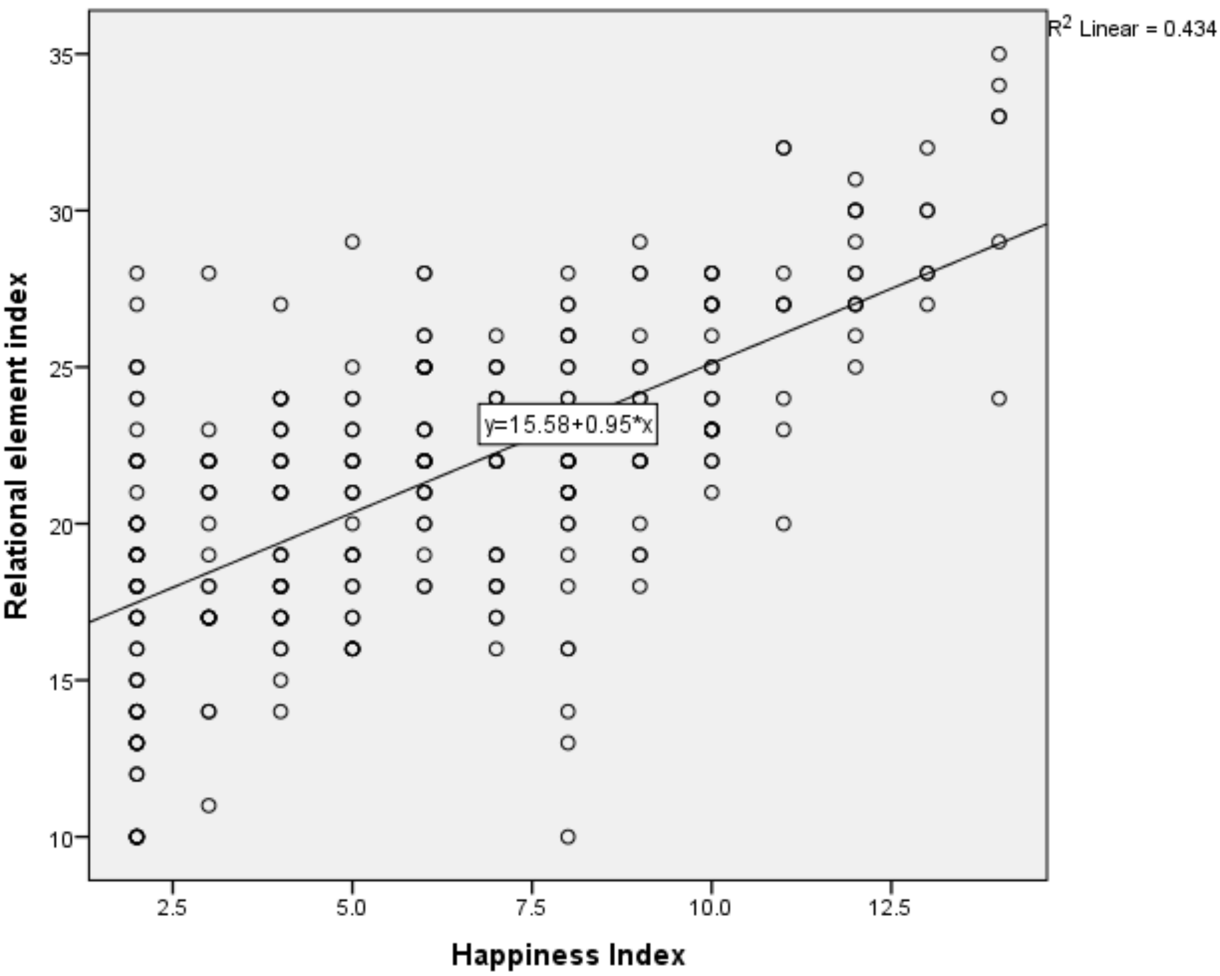
Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	9.177	.642		14.299	.000
	Guilt Index	.565	.028	.754	19.844	.000

a. Dependent Variable: Relational element index

Regarding **H6 –Happiness**

Scatter Plot of Happiness Index and Relational Element Index.



ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	3064.709	1	3064.709	229.655	.000[b]
	Residual	3990.115	299	13.345		
	Total	7054.824	300			

a. Dependent Variable: Relational element index

b. Predictors: (Constant), Happiness Index

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	15.576	.437		35.643	.000
	Happiness Index	.954	.063	.659	15.154	.000

a. Dependent Variable: Relational element index