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Exploratory and Empirical Investigation of AI in Social Media Customer Care

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To Fiorenza and Lino. This journey would not have been possible without your sacrifices.

To Vittorio. My passions derive from your teachings.

To Elena. We learn and grow together.

To the WEF Global Shapers Community.

To Alberto, Edoardo, Francesco, Iacopo, Luca, Roberto.

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Introduction: Social Media Customer Care and AI

Social media has developed a central role in customer service (Barnhart, 2021). There are multiple reasons. Guo et al. (2020) specify that adopting social media-based consumer support allows organisations to conduct services such as gathering client feedback, troubleshooting customer issues, treating consumer requests and easing the exchange of consumption experiences among clients. For example, Nike and Spotify have taken advantage of Twitter to establish accounts dedicated solely to customer service requests (Chan, 2020); Amazon is developing solutions on social media to answer consumer queries in their native language (Thomas, 2020) and Zappos ensures it provides customer help on social media within 20 minutes from a query post (Wix Answers, 2019). In addition, Guo et al. (2020) underline that customers can collect product information and find solutions on common issues via social platforms.

To fulfil such benefits, companies created dedicated customer support teams on social media replying to consumer requests (Xu et al., 2017). Yet, manually addressing service enquiries is time-consuming and brands often fail to meet clients' expectations. Social media has conditioned clients to receiving fast replies (Benmark et al., 2012). In fact, 61 percent of customers prefer to obtain a reply from self-service or automated technology rather than wait to speak with a human agent (Sherlock, 2009). Moreover, 40 percent of consumers expect brands to reply within 60 minutes, 79 percent require an answer in the first day (Barnhart, 2020). Even though various tools are available, systematic, technically integrated solutions, that ensure monitoring of service requests and direct responses on social media platforms, are limited (Geierhos, 2011).

In this context, artificial intelligence is a powerful method to deal with service failure and reduce client churn (De Kyser et al., 2019). The reason is the technology's ability to interpret data, learn from such information and use those learnings to complete or adapt to specific tasks (Kaplan et al., 2019). For example, Forbes (2021) suggests that artificial intelligence can solve most frequently asked questions and speed up response times. In the former case, providing a solution to 50 percent of enquiries improves user experience. In the latter case, it can identify customers' needs and suggest potential solutions to human agents. Investments in technology are increasing and around three executives out of four believe that AI will deliver more efficient business processes (McKendrick, 2021). However, organisations are finding AI difficult to adopt in core practices (Fountaine et al., 2019). For example, organisations do not fully understand the benefit of the technology for the customer experience or pose questions on AI's

ability to provide satisfactory responses (Goasduff, 2019). Moreover, AI relies on customer active interaction, which raises service complexity and could lead to service failure (Hilton et al., 2013). As consumers are required to invest more effort and attention on the interaction, the risk of frustration or annoyance could increase when support fails to provide effective assistance (Castillo et al., 2020). Forbes (2017) also suggests that AI presents limitations linked to errors in valuation of consumer requests. Though algorithms fail percentage is limited, this could result in subpar experiences for a number of clients.

The abovementioned interest on AI in social media customer care is reflected in academic research. Yet, papers are recent and limited in number. Different studies have focused on developing AI systems within the domain of data analytics (Xu et al., 2017 and Ozonat et al., 2012). In particular, such field of research described automated chatbots and algorithms to extract words and learn preferred answers for support questions. Others have reflected on the classification and identification of emotions in social media customer requests (Herzig et al., 2016 and Hu et al., 2018). In this context, Agnihotri et al. (2021) specify AI is not suitable for customer care as it lacks ability to answer with empathy, i.e. in a similar manner to a human agent. In addition, research by Ghouri et al. (2022) and Overgoor et al. (2019) have focused on providing logical stages for delivering effective customer service via AI in social media. Academic studies also have described the ethical and legal issues that have to be taken in consideration for the use of AI when answering public requests for help (Lewis et al., 2020 and White et al., 2020). While these endeavours provide a diverse analysis of AI in social media customer care, there is limited attention to design elements and to maximisation of positive customer experiences. In fact, Hu et al. (2018) suggest that further research is necessary to understand end user engagement with AI agents. Hazée (2021) specify that analysis is needed to understand the impact of AI agent disclosure within an organisation's support service. The author adds that further studies are required to estimate the role of context and brand image on the use of AI. Moreover, Ghouri et al. (2022) also describe that examination of AI in social media should be carried out from perspectives other than executives and managers of well-established corporations. In consequence, there is limited comprehension of AI design elements in social media help requests and in particular inadequate attention to consumer perception of the technology.

Whilst organisations require a clear understanding of benefits that AI ensures for customers, academia has centred on developing theoretical knowledge or analysed specific characteristics of the technology. Therefore, this master thesis proposes to examine the impact of AI on social media customer care. In particular, it adopts a novel focus by analysing consumer insights and

perspectives on the technology. The intended contribution of the study is threefold: establish the boundaries of current knowledge on AI in social media customer care, define which characteristics of the technology favour consumer satisfaction via interview, verify such assumptions through empirical research.

The thesis is divided into four sections. First, it defines customer service and provides an overview of satisfaction drivers. It also highlights the consequences of the increasing adoption of social media. The objective is to create a theoretical background and underline which focus points are most relevant to create value for a client. In addition, the thesis defines the state-of-the-art of literature on AI and social media customer care. The discussion serves to provide a framework that defines the most relevant characteristics of the technology in the context of social network platforms. The two sections identify rules and limitations of current academic literature about technological support in social media.

Second, the thesis aims to connect the abovementioned knowledge identified through theoretical research to insights from clients and consumers. A set of fourteen interviews is carried out to analyse customer experiences and interactions with support services and artificial intelligence in social media. In detail, meetings are conducted on a sample of individuals that have encountered or can relate to AI agents whilst requesting support on network platforms. The identified design elements and propositions serve as input for further research on AI in customer service within social networks. The thesis interest rests on audience attitude towards AI agent disclosure and brand image.

Third, hypotheses on design elements are defined and checked through an empirical quantitative analysis. This is conducted via a survey, which reached 278 individuals. Two hypotheses were verified across 4 separate factors, 2 per each design element. Based on the exercise, theoretical and managerial implications were analysed. The objective is to identify how the current thesis contributes to the academic and business knowledge.

Fourth, the study concludes by summarising findings and defining the limitations of the analysis. In addition, a number of future research questions are identified to enable other academics to further develop the field.

Review of Literature: Overview of Customer Service

This thesis aims to expand academic research on the impact of AI in social media customer care. To answer such research question, it is necessary to elaborate a theoretical background on the two objects that are central to the analysis: customer care and AI.

This section introduces the reader to the topic of the customer service and defines the underlying structures that impact this field of marketing. Then, it delves into customer satisfaction by defining the key characteristics of customer service quality and consumers' relative expectations. As specified in the introduction, this serves to focus the thesis on consumers' perspective. In addition, customer satisfaction will be central to the hypothesis development. Finally, this segment introduces the role of social media networks, their opportunities and challenges within customer service.

Customer Service and Customer Care

The supply of outstanding customer service has developed into a competitive advantage and a central competency towards which most corporations aspire (Groth et al., 2018). This ambition to deliver high-standard support has increased the appeal to investigate the interaction between customers, service agents and corporations (Subramony, 2017). The quality of relationship among service agents and consumers is a key component of the service experience; yet the largest part of service provision is intangible and dependent on the personal understandings of the client or employee (Groth et al., 2018). Therefore, the social exchange, i.e. the moment of truth in which a client forms a connection with the employee and company (Bitner, 1995), has been recognised as a fundamental contact point for organisations to understand and manage. The result is that a customer-centric view of support dominates academic literature and forms the basis of popular understanding on service experience (Groth et al., 2018).

In the context of service experience, this study provides a theoretical distinction between customer service and customer care. This is relevant as it analyses the first of two components in the research question.

Customer service is defined as advice or assistance offered to a client (Morgan, 2018). It refers to providing support on the most appropriate use of a product, responding to enquiries and solving issues, ensuring a positive purchase experience. Morgan (2018) specifies the interaction could occur both before and, typically, after the completion of an acquisition. Fontanella (2022) confirms this definition and refers to customer service as simple advice or assistance. In contrast, customer care describes how clients are treated when interacting with a

brand (Morgan, 2018). It entails caring for the consumer, listening to its requests and developing a suitable solution. Therefore, customer care complements customer service by considering the emotional connection with the client (Fontanella, 2022).

For the purposes of this thesis, customer service and customer care define the activities that enable clients to reduce trouble from utilisation of a product and gain support in case of questions, issues or doubts (Goffin et al., 2021). The two terms, i.e. customer service and customer care, are utilised as synonyms. The reason is that this definition reflects the common perception of support, thus limiting comprehension barriers in future experiments.

In management, Dresner et al. (1995) propose that increasing investments and efforts in customer service is directly related to increasing economic performance and customer satisfaction. In line with the dominant literature view of customer-centric service, additional factors must be considered. Beaujean et al. (2006) affirm that customer service entails handling frontline answers as to prioritise clients' emotional requirements over the organisation's and worker's agendas. This rationale is required in unconventional interactions with consumers. For example, providing quick support in reservation and check-in would be considered more relevant in the airline sector compared to traveller's checks (Beaujean et al., 2006). Any corporation, in a given industry, can identify emotionally charged requests and ensure its investments are directed towards such interactions and towards maximising positive exchanges. In addition, customer service requires employees to have a positive outlook, promote constructive replies, be aware of human agent's and client's feelings to reduce anxiety related to the interaction or need for a solution (Beaujean et al., 2006). Such objectives can be accomplished through diverse communication channels. Physical locations, such as shops and branches, are attractive interaction solutions for customers (Bekier et al., 2000). However, these are more expensive than other channels, including call centres and internet platforms (Durkin et al., 1999). Other typical communication solutions include emails, communities and forums, mobile messaging (Smith, 2022). However, it must be noted that customer service across multi-channels poses significant difficulties in staff and process coordination, which might lead to structural changes in the company's organisation and in the behaviour of consumers (Hughes, 2005).

Customer requests for support vary in their nature. Basic transactional interactions involve requests on balance, address changes, product purchase or service activation (Dixon, 2018). In these circumstances, consumers are focused on retrieving general information. In addition, clients might contact an organisation to solve complex and varied problems linked to their offerings (Dixon, 2018). This could entail negative complaints or product breakdown that have

urgent priority for the client. Delivering a positive support to these requests has diverse benefits. Innis et al. (1994) explain that higher customer satisfaction after service interactions is positively related with higher market share. Bielenberg (2006) specifies that positive client support leads to increased sales and loyalty. In contrast, negative efforts reduces client happiness leading to delay or withhold of payments (Bielenberg, 2006), thus reducing cash flows and potentially increasing debt. Moreover, Growth et al. (2012) sustain that negative service encounters lead to open-loop spirals in which subsequent clients experiences are also negatively affected.

Customer Service Satisfaction and Service Quality Measures

Customer service influences the overall brand experience and contributes to ensuring satisfaction after the sale has concluded (Kotler et al., 2013). Although many organisations have attempted to measure customer satisfaction via available data, the mere measurement does not ensure clients will be satisfied after an interaction with the firm (Schwager et al., 2007). Yet, research on customer satisfaction has identified clear consumer expectations on service-delivery, including emotional components (Groth et al., 2018). Therefore, this section of the study provides a review of consumer satisfaction in support requests. It serves to centre the analysis around the perspective of clients and to provide a summarisation of expectations in modern customer service. As a key parameter and measuring point for the evaluation of service (Cengiz, 2010 and Adhitya et al., 2021), consumer satisfaction will form the basis of hypothesis testing and empirical quantitative analysis in this thesis.

Customer satisfaction originates from the client's evaluation of an experience (Özkan et al., 2019). And it is defined as an individual's sentiment of pleasure or disappointment as a result of comparison between a service's perceived performance and the individual's expectations (Kotler et al., 2013). In further detail, expectations are interpreted differently by service quality and customer satisfaction literature (Dean, 2004). In the former field, expectations assume a normative role, are grounded on past experiences and describe a client's view on what should occur. In the latter field, expectations are linked to what clients predict, they are grounded on future experiences. The reader should note that this is the adopted definition of expectation for this thesis. Moreover, Parasuraman et al. (1991) identified that customer service expectations have two different levels: desired and adequate. The desired service is the support that the client wishes to obtain. It is the point of equilibrium between what support can be and should be from a customer perspective. The adequate service is what the customer deems satisfactory. It represents the customer forecasts. According to the author, support expectations, and therefore

client satisfaction, are included in the zone of tolerance between the two levels mentioned above. Kadłubek et al. (2015) expand the above explanation by stating that service satisfaction also depends on the manner in which a support is delivered. This is also reflected by Eisingerich et al. (2008). The authors sustain that customer satisfaction depends on the technical and functional quality of a service. The first is the quality of the support output; the second is the extent to which an agent provides considerate, relevant service and empathises with the client's conditions. In fact, the authors demonstrate that customer satisfaction in service depends on the creation of effective relationships between the client and the brand, i.e. support should demonstrate care, feelings and should educate the client on the product that caused the support request.

According to Parasuraman et al. (1991), customer service expectations are grouped into five dimensions: reliability (the capacity of a brand to deliver an expected service dependably and accurately), tangibles (the use of equipment and communication tools), responsiveness (the ability to provide prompt support), assurance (the kindness, trust and confidence transmitted during support), empathy (the care demonstrated and personalisation of service). In their research, the authors demonstrated that customers valued reliability over the other dimensions when evaluating customer service. In a similar fashion, Dixon et al. (2010) suggest that customer satisfaction depends on reducing the client's efforts, i.e. the work that must be completed to solve the issue at stake. The authors affirm that brand deliver satisfactory service by solving help requests quickly and easily. In fact, clients begrudge contacting a corporation in diverse occasions or be bumped between communication channels. This is confirmed by Parasuraman et al. (1991), who affirm that consumers expectations are mostly concerned with fundamental services. Dixon et al. (2010) suggest a second indicator of customer satisfaction: empathy. In their study, 20 percent of repeated service requests resulted from emotional disconnection between the service agent and the client. This occurred when consumers did not trust their respondent, did not appreciate the answer or perceived they were provided with general company policies rather than specific help. Note that as customer satisfaction depends on the experience of the client, it is subject to relative interpretation. In fact, Steven et al. (2012) demonstrate that customer satisfaction depends on the level of service itself. When low service is delivered, increases in support produce significant improvements in satisfaction. On the contrary, satisfaction changes are less noteworthy at high service levels due to diminishing returns.

Recent analysis confirms the above priorities in customer service. Consumer satisfaction is linked to the provision of basic support, namely, to feel heard, to solve the issue with ease, to

see action being taken on the request, for action to be quick (Sellers, 2021). In detail, the author affirms that 58 percent of consumers today require to be valued and appreciated. The reason is that a request for support is perceived as a personal transaction between themselves and the brand (Sellers, 2021). The expectation of prompt, friendly and personalised service is also confirmed by Marsden et al. (2022). A research by Puthiyamadam et al. (2018) demonstrated that speed, convenience, knowledgeable help and friendliness are paramount for 70% of consumers. For example, more than half of consumers would abandon a brand after unfriendly service or experiencing bad attitudes from human agents. Moreover, Marsden et al. (2022) add that ethics and purpose are considered central for clients when selecting a specific organisation in the market.

Another key dimension to customer satisfaction is speed. Benmark (2012) shows that 33 percent of customers would prefer fast but ineffective responses to their issues, against 17 percent who would prefer slow but useful advice. Silva (2021) explains that the current age of instant gratification has affected client expectations who value instant results over premium costs.

Other relevant evaluations of customer support are service quality and repurchase intention. Whereas satisfaction refers to specific transactions, service quality is concerned with global judgements and attitudes towards support (Parasuraman et al., 1988). The dimensions of service quality have been proposed by Sasser et al. (1978). These material, facilities and personnel. The authors evaluate service not merely for the outcome, rather they also include the way in which support is provided. Gronroos (1982) confirms this idea by identifying two key dimensions of quality: technical, i.e. what the client is concretely receiving as a support, and functional, i.e. how the psychological interaction between the company and customer occurs. Lewis et al. (1990) add another element to the analysis by suggesting that corporate quality, intended as brand image, affects service. Finally, Gronroos (1990) added another dimension in recovery and LeBlanc et al. (1988) stressed the role of physical support in the organisation as a determinant of service.

Repurchase intentions is the intention is the willingness of a client to reacquire a product or service in the future (Filieri et al., 2017). This is also referred to as customer loyalty (Cossío-Silva et al., 2016). When a consumer has performed a predetermined number of acquisitions, the company has achieved the client's expectations (Adhitya et al., 2021). Customer satisfaction has a significant impact on repurchase intentions (Liao et al., 2017). In fact, satisfied clients after receiving service support help build sales and are more loyal, thus directly influencing repurchase intentions (Larivière et al., 2016).

Customer Service and the Rise of Social Media

Customers are increasingly overcome by the number of self-service channels – including voice responses, chats, social media – and often lack the knowledge to select the most effective solution (Dixon et al., 2010). Therefore, they tend to opt for the solution that is more convenient, simple and interactive (Bianchi et al., 2015). In addition, consumers in digital customer service are driven by the need to create social connection and co-operation with the brand's agent (Sheehan et al., 2020). Similar expectations are present in social media customer care. In this context, this section of the thesis centres on the rise of social media. Its objective is twofold. First, it aims to understand the consequences of social media as a communication channel for service requests and customer satisfaction. Second, it describes the challenges and opportunities that derive from the development of the technology.

Client support in social media, i.e. technology-based ecosystems in which public or private persons and organisations exchange different and complex behaviours, interactions and exchanges (Appel et al., 2020), is administered and executed differently compared to traditional service communications. Whereas conversations via phone or website involve a direct relationship with an agent, social networks are indirect and facilitated by third parties online (Yadav et al., 2014). In addition, network platforms communicate mostly via text and enable repeated readings, thus creating a lasting list of posts (Moffet et al., 2021). In addition, client networks and algorithms based on information sharing increase the probability that interactions are viewed and read by a larger audience relative to traditional client service channels (Golmohammadi et al., 2021). Therefore, one interaction might generate or lose customers (Sparks et al., 2016). The diverse impact of social media is also demonstrated by Van Vaerenbergh et al. (2019). The authors affirm that interactions with clients might occur at different points of the customer journey, which might be comparably relevant in creating new relationships.

Consumers utilise social media to reach both companies and other consumers for sharing negative (including criticisms and issues), neutral (including questions and doubts) or positive feedback (including praises) (Hazée, 2021). Criticisms or product problems are valuable learning points for companies and require quick responses as well as solutions to avoid losing clients (Van Vaerenbergh et al., 2019). In fact, Das et al. (2022) showed that if consumers do not receive a reply on social media after a bad experience, 81 percent will not recommend the company to acquaintances. Questions and praises do not typically necessitate detailed answers and must be adapted to the message sent by the customer (Chen et al., 2019). Moreover, public replies to negative and positive posts affect future interactions with clients differently, by

prompting or mitigating further communications (Chen et al., 2019). For example, Adhitya et al. (2021) demonstrate that customer reviews on social media do not have a significant effect on customer satisfaction. Another consequence of social media customer care is that consumers publicly praising a company via posts develop higher expectations for service support (Bozkurt et al., 2021). The reason is that customers understand they are offering public advertising.

Academic literature on the dimensions that determine satisfaction for customer support in network platforms is scarce. Hu et al. (2019) argue that kindness affects the customer's tendency to develop positive or negative perception of support services. Mousavi et al. (2020) state that client satisfaction within social media care depends on the quality of the content received and on the responsiveness of the answer. Professional literature has identified two main expectations from clients: quick response and human approach. The majority of consumers expect a reply on their issues published in social media within the first day and less than half require a response in the first hour (Amaresan, 2021). Facebook users, which accounts for three quarters of all social media complaints (Baer, 2021), are satisfied if a response to an issue is received in the first 30 minutes. Fontanella (2021) also suggests that consumers require a reply to negative comments within the first week. Moreover, Caramela (2021) points that client satisfaction is obtained by offering responsive and attentive customer support on social platforms. The former indicates that clients expect brands to answer their issues and be active in attempting to solve it. The latter indicates that organisations are required to actively listen and avoid misinterpretations of the problem presented. In addition, Deloitte (2021) points that customers expect to be treated through a human, individual approach and require their loyalty to the brand to be rewarded through appreciation and comprehension. This is confirmed through experimentation by Herzig et al. (2016). The authors suggest that affective components and emotion expression in social media are a reasonable predictor of customer satisfaction.

Table 1 shows that customer service satisfaction and expectations do not vary across traditional and social media client service. In particular, there are three recurring themes that have to be considered in customer care: speed, human approach, reliability.

Customer Satisfaction Variable	Definition	Number of References	Number of References in SMCC
Reliability	The capacity of a brand to deliver an expected service dependably and accurately	4	1
Responsiveness	The ability to provide prompt support	5	4
Empathy	The care demonstrated and personalisation of service	5	4
Tangibles	The use of equipment and communication tools	1	-
Communication of Service	The level of service affect satisfaction and client expectations	1	-
Ethics and Purpose	The level of morality displayed by customer services	1	-

Table 1. Customer Service Satisfaction Review

Social media as a customer care tool presents significant opportunities for companies. To start with, it allows for economic gains. Utilising network platforms costs on average one US dollar per interaction, compared to six per phone call or four per email (Benmark et al., 2012). Moreover, the authors suggest that around 30 percent of consumers prefer to use social media rather than calling customer service and that clients with positive experiences on network platforms are three times more probable to recommend the company (Benmark et al., 2012). Das et al. (2022) suggest that client purchase 20 to 40 percent more on brands that reply to queries on social media. Guo et al. (2020) suggest find that the larger the amount of social network channels a brand utilises, the higher the reputation gain. ENP Newswire (2015) provide conceptual opportunities for social media support. It suggests that network platforms ease the process of collecting consumer insights and feedback, promote marketing campaigns by sharing links or information in responses and increase advocacy.

Despite the benefits of implementing customer service on social media, unique challenges still arise for companies. Benmark et al. (2012) propose four pain points. First, organisations have to establish if social media increases the value of support services and lowers costs of operations according to the risk from public conversations, position in the marketplace and regulation restrictions. Second, employees or algorithms require extensive training programs and guidelines to ensure positive customer experience, brand advocacy and sales. Third, create a test system to determine which queries or complaints can be answered in public posts (for example, if the answers is beneficial to multiple users) or necessitate a private interaction (for example, if the answer entails the exchange of personal information). Fourth, companies must build a set of key performance indicators that centres on customer satisfaction.

Another challenge is represented by the pace of digital technologies, which offers consumers increasing opportunities to access untact, i.e. no face-to-face contact, service and interact with companies on social media (Lee et al., 2020). And companies need to adjust their communication style according to the social media platform (Das et al., 2022).

Review of Literature: AI in Social Media Customer Care

Despite the growing interest in academia and business, research on AI in social media customer care remains limited. This points to the necessity to delimit the boundaries of AI's functionalities, highlight what is currently known in relation to social media client support and derive further directions of analysis.

Definition of AI

This section of the thesis explores the definitions of AI available in academic literature. It lays the theoretical background to investigate the research question on the impact of artificial intelligence in customer service within network platforms.

Russell et al. (2018) describe artificial intelligence as the investigation of general principles guiding rational agents and of components for developing them. Poole et al. (2010) employ a similar characterisation of artificial intelligence. In fact, they describe the technology as computational agents that operate intelligently in action. In these definitions, agents include any system capable of understanding the reality surrounding themselves and reacting by means of such understandings. In further detail, rational agents are defined as those that act with the objective of reaching the favoured solution or, when uncertainty characterises a decision, the best expected solution. Russell and Poole focus on the marketing perspective of the technology: they stress its capacity to provide the best decision within a set of given data (Overgoor et al., 2019). In this regard, marketing is defined as the activity and processes that create, deliver value for consumers (American Marketing Association, 2017). Moreover, the authors negate artificial intelligence's emulation of human abilities as rationality provides for easier scientific assessment. Yet, the intersection between marketing and social sciences has placed increasing focus on consumer's psychology (Mariani et al., 2021). In fact, Huang et al. (2021) suggest that artificial intelligence involves the usage of computational technology to mimic social abilities, including thinking and feeling. This definition is aligned with the analysis of consumer satisfaction depicted in the above sections of the thesis. In fact, this study portrayed empathy as a key determinant of satisfaction in client support. Note that the two divergent definitions of artificial intelligence reflect the historical distinction between weak and strong AI (Bechmann et al., 2019). The former is a tool to examine consistent amounts of information in a more rigorous and precise manner than human brains would do; the latter is a tool to imitate human behaviour and communication (Searle, 1980). At first glance, social media requires

strong AI as algorithms must decode human conversations as well as tones and adapt to relative modifications (Bechmann et al., 2019).

AI in Marketing

This section further explores AI as a tool in marketing. It proposes a literature review to highlight the use of the technology in the abovementioned field of study and defines what are the benefits as well as challenges of its adoption. Within the context of the research question, i.e. AI in social media customer support, this segment identifies how the thesis elaborates and contributes to current academic knowledge.

Marketing is defined as the task, group of institutions and processes to create, communicate, deliver and exchange products or services which possess worth for customers, clients, partners and society (American Marketing Association, 2017). This discipline has rapidly transformed in the last decades as a result of technological advancements. In fact, the Marketing Science Institute proclaimed AI as a research priority for the field in the period between 2020 and 2022. The organisation affirms artificial intelligence will impact the definition of marketing capabilities and improve marketing functions as well as strategies (Marketing Science Institute, 2020). Further confirmation of the relevance of AI in marketing is provided by Mariani et al. (2021). The authors investigated the number of scholarly publications about AI in marketing and identified an exponential growth over the last decade: around 54 percent of research between 1972 and 2021 on the topic was published after 2017.

Huang et al. (2018) offer an overview of the use of AI in the context of the job market. They highlight the roles of the technology and its impact on labour demand by identifying four intelligences. These represent four different goals to be achieved by AI. Huang et al. (2018) propose an analysis of AI that is not technical, rather it defines the general abilities of the technology.

The first intelligence is mechanical. This represents the capacity to execute routine, repeatable tasks (Huang et al., 2018). In this scenario, AI has limited learning and development potential. It operates through a priori competences and information gathering to react in a consistent, repetitive manner. The second intelligence is analytical, i.e. the ability to understand information and deliver relative solutions (Sternberg, 1984). Machine learning and data analytics allow algorithms to discover insights without being programmed to search a specific type of data. This enables to carry out complex, yet consistent, tasks. The third intelligence is intuitive. It refers to AI's creative thinking and adjustments to unprecedented occurrences (Sternberg, 1984). The technology learns intuitively and emulates human cognition, such as

self-awareness and consciousness. The final intelligence is empathic, which identifies the ability to recognise and process emotions (Goleman, 1996). This is possible as emotions are compared to cognition and can be programmed in a computational manner (Huang et al., 2018). Examples of this ability are limited but AI could be used to provide psychological comfort or support, as in the case of Replika (Huet, 2016).

Davenport et al. (2020) expand the framework above by identifying AI uses based on two different categories of analysis: task automation and context awareness. The former identifies current uses of the technology, the latter future developments (which are not of interest for this thesis). The authors highlight four functions of AI in task automation. The first is artificial intelligence as a controller of numeric data. This involves statistical analysis of information through machine learning techniques. For example, companies utilise algorithms to optimise prices between a threshold low enough to attract clients and high enough to guarantee sufficient profits. The second is AI as controller of data, i.e. the analysis of non-numeric data, such as speech and image recognition through neural networks, to improve understanding of clients' needs and potential customer service improvements. The third and fourth are artificial intelligence as numerical data and data robots. This resembles the two previous uses but are delivered in a robotic form.

In contrast, Vlacic et al. (2021) conduct a systematic literature review on marketing and AI. The authors have identified 164 publications from Web of Science and Scopus indexed journals via multiple correspondence analysis.

Theme 1 is marketing channels. Vlacic et al. (2021) define marketing channels as the link between the producer and consumer. They highlight that a number of articles focus on increasing efficiencies in marketing channels through algorithms. Artificial intelligence is capable of gathering and interpreting unstructured data in an intelligent manner. This allows corporations to identify client demographics and psychographics which result in improved customer segmentation and predictions of consumption. In addition, AI has been utilised as an alternative marketing assistant as it is capable of processing language and recognising pictures from multiple data sources. Such ability to extract information and advise on client characteristics enables better online targeting (Vlacic et al., 2021).

Theme 2 is marketing strategy. According to research by the authors, AI has contributed to improving business model decisions (including the identification of new solutions combining niche and mass market strategies), product development, communication, pricing, sales, advertising. Moreover, algorithms have been utilised to review workflows. In fact, routine or simple tasks can be standardised and completed by technology.

Theme 3 is performance. In this context, AI's contribution is two-fold. The technology is able to improve predictions and manage complex, non-linear relations between inputs and outputs (Russell et al., 2018; Syam et al., 2018). Artificial intelligence also delivers competitive advantages in sale performance and value creation for customers. The analysis of big data allows to estimate customer lifetime value, purchasing patterns and trends in demand.

Theme 4 is segmentation, targeting and positioning. In marketing, AI is used to anticipate shifts in clients' demographics, psychographic, behavioural and geographic segments. In addition, the use of artificial neural networks allows improved identification of market segments compared to discriminant analysis or logistic regression (Fish et al., 1995). Furthermore, AI supports in the prediction of customer churn (Wei et al., 2002).

Huang et al. (2021) propose a strategic framework of artificial intelligence in marketing. It combines the recognition of AI intelligences, as in Huang et al. (2018), with the identification of AI uses solely in marketing, as in Vlacic et al. (2021). In fact, the authors conceptualise artificial intelligence to have multiple intelligences for various tasks. In order of difficulty of execution, these are mechanical, thinking and feeling. Mechanical AI serves to complete routine and repeatable actions, such as clustering, classification, machine translation. Thinking AI serves to process, typically, unstructured data and derive relevant decisions. Examples include pattern and image recognition, text mining. Feeling AI requires an interaction between a human expressing emotions and the technology itself. Applications include natural language processing, neural networks and chatbots mimicking human speech.

The three intelligences serve Huang et al. (2021) to categorise AI uses in marketing research, strategy and action. Mechanical AI is employed in the research stage of marketing to automate data collection on the market, environment, firm, competitors and customers (Huang et al., 2021). These are routine tasks that can be applied both to observable data and data gathered via survey or experiments. Instead, thinking AI is utilised for market analysis, such as competitor detection and definition of a product's competitive advantages. This can be carried out through automated text analysis of machine learning in social media websites. Finally, feeling AI serves for customer understanding, which is the recognition of customer needs and desires as well as their feeling and attitudes.

The strategy stage in marketing is divided by Huang et al. (2021) in three components: segmentation, targeting and positioning. Segmentation entails the division of the market into sections of customers with comparable desires and responses to marketing action (Tarver, 2022). Mechanical AI enables to spot patterns of data through mining or grouping, which might be difficult to process for humans. Targeting entails identifying a group of potential customers

for marketing actions (Investopedia, 2022). This represents thinking AI as it requires domain knowledge and intuition to select the appropriate segment (Huang et al., 2021). An example is predictive modelling. Positioning involves feeling AI as it necessitates the evaluation of customer perceptions and communication to maintain the desired brand image.

In the action stage, artificial intelligence serves for standardisation (mechanical AI), personalisation (thinking AI) and relationalisation (feeling AI) (Huang et al., 2021) of the 4Ps. The role of marketers is to identify which intelligence is best suited for each marketing action. For example, mobile payments and delivery can profit from standardised processes such as automatic payments and delivery tracking; whereas digital marketing can profit from personalisation as it allows to customise communications for each customer profile online.

Mariani et al. (2021) utilise the bibliographic coupling to develop a systematic literature review of AI in marketing, consumer research and psychology. This expands the review of Vlacic et al. (2021). The technique computes the similarity between papers by defining the number of shared references (Kessler, 1963). The references represent a guidance to the topic tackled in an article and, therefore, links articles with similar research propositions (Perianes- Rodriguez et al., 2016). This results in visualisation maps that highlight the most cited research and, in consequence, the most relevant topics of study (Jones et al., 2014). The analysis conducted by the authors was based on 198 documents, each counting at least 100 citations, divided in eight clusters.

The first cluster concentrates on three cognitive processes that humans can perform. To start with, Wilson (1988) proposes AI as a tool to create psychological and linguistic descriptions of words processable by machines and collectable in a dictionary. Similarly, Perry et al. (2007) define various computational models as instruments for reading and word recognition. Then, Thagard (1989) proposes a theoretical model to explain casual reasoning, enable the rejection of statistical hypotheses and processes decisions. Mariani et al. (2021) recognise that this work offers a link between psychological and technological applications of casual reasoning. Finally, AI serves to process visual images, select relevant pixel inputs and recognise images. This research field was analysed by Pylyshyn (1999) and Frintrop et al. (2010).

The second and third cluster focus on reasoning and cognitive processes. The former relates to decision making and cognitive processes required to understand human brain functionalities. Mariani et al. (2021) identified that research in this field is scarce. Further exploration is required to link AI processes to the brain's ability on developing response rules, build knowledge through intuition and memory. The latter cluster focuses on neural networks. In this

context, AI supports in recognising images, such as human faces, form personality and temperament, examine attention.

The fourth cluster is relative to machine learning and linguistic capabilities. The authors provide a brief explanation on incorporation of computer science principles in psychology. This is not relevant for scope of thesis. Yet, they also point out that several documents have highlighted the role of technology in natural language processing. For example, machine learning can analyse speech and cognitive styles to understand consumer sentiment. This is reflected in the paper by Pennebaker et al. (2003), who suggest that speech particles are an indicator of emotion and social identity.

The fifth cluster concentrates on the relationship between user-generated content, in online social network platforms, and marketing decisions. Articles and research in this topic aim to analyse large amounts of unstructured data in blogs, online websites and social media via text mining techniques. Mariani et al. (2021) cite three examples. Netzer et al. (2012) develop technology to detect patterns in online forums. Goh et al. (2013) and Archak et al. (2011) examine the impact of social media and sentiment, respectively, on future purchase behaviours. The sixth cluster refers to social media analytics as a source of consumer insights for decision making in marketing. The authors suggest that AI algorithms improve predictive capabilities in defining which experiential elements or content on social media improves satisfaction and support organisations in identifying preferred product development of customer segmentation. The seventh and eighth cluster refer to research on the acceptance and adoption of AI. This concerns the role of occupational status, gender, personality towards robots and the ability of algorithms to perform complex tasks autonomously in the service industry.

The analysis above suggested numerous advantages for the use of artificial intelligence in marketing. A summarising position is offered by Davenport et al. (2020). The authors affirm that artificial intelligence allows optimisation of marketing process and improved comprehension of customer needs. They add that technology allows to analyse unstructured data from social media or websites. This could potentially result in increased customer engagement (Davenport et al., 2020). A different perspective on the benefits of AI is offered by Pitardi et al. (2021). They suggest that consumers prefer AI as a service agent in interactions they perceive as embarrassing. The reason is that algorithms are not capable of forming judgements and thus customers are less inclined to experience negative emotions, including shame or fear. Yet, a number of challenges still apply for AI in marketing. Data collection from customer interactions poses significant ethical and privacy concerns (Ameen et al., 2020). Companies should request the client's permission to take advantage of their information and

should abide to data protection regulation (Butterworth, 2018). Furthermore, Vlacic et al. (2021) question what the acceptability of AI is and what relational elements derive from interactions with it, including the level of trust from consumers. The authors also ask what the role of emotions in the adoption and use of AI is as well as what the consumer characteristics that impact the attitude towards the technology are.

This thesis aims to contribute to existing literature by analysing the role of AI in social media customer care. Despite limited observations on the impact of artificial intelligence as a service assistant, academic articles have rarely investigated its relation to online social platforms. Therefore, the following sections propose to review existing publications on the field via a conceptual framework and define which research questions are left unanswered.

Methodology

Though the literature review in this thesis is selective, a specific protocol is developed to ensure the identification of relevant papers. The collection of literature stems from the research question, i.e. what the impact of AI on social media customer care is, and multiple databases, including Google Scholar, UCD Library, UCLouvain Library, Springer, Web of Science. Note that a number of journals were also consulted, for example: Journal of Business Research, Cornell Hospitality Quarterly, International Journal of Hospitality Management, Tourism Management, Computers in Human Behaviour, Journal of Interactive Marketing. This list was selected based on Hazée et al. (2021) systematic literature review process.

To increase the effectiveness of research, a number of articles and business reviews were consulted to familiarise with the research topic. This generated a list of words frequently utilised: artificial intelligence, chatbots, automation, natural language processing, social media customer service, social media customer support, digital customer service, online corporate response strategies. The use of connectors – such as *and*, *or*, *in* – and combination of key words above created different strings. Examples include artificial intelligence and social media customer care, chatbots in digital customer service. Papers were selected if the keywords were included in the title or abstract. The literature review was conducted at the start of 2022.

This process identified around 14 000 papers. To reduce complexity and increase relevance, the research excluded all non-English articles and any work that focused on specific criteria such as electronic word-of-mouth, analytics, data mining. In addition, literature was excluded based on the date of publication: articles or university publications were not considered if published before the last decade. The reason is to confront works which refer to similar consumer needs and are affected by comparable socio-economic conceptions. This is of

particular relevance if one considers that AI has witnessed an earlier wave of research and interest towards the second half of the last century (Anyoha, 2017). If a paper was deemed relevant, its reference list was consulted to find similar sources.

The above process resulted in 76 articles, though only 7 were strictly related to the use of artificial intelligence in social media customer care. Then, a conceptual framework was created to identify the key macro fields of study that impact outputs of AI in social media customer service. In detail, the categories identified through literature analysis are design elements and consumer behaviour. The reader should note that academic and professional work was analysed by presenting and evaluating the various perspectives of the authors. In this context, an extraction table was developed to compare current academic knowledge and the contribution of the present thesis. This exercise compared theory presented, findings, methodology. Furthermore, the following review utilises the terminology customer care and customer service, social media and network platforms (or variations) as synonyms.

AI in Social Media Customer Care

This section serves to relate the definition of artificial intelligence to social media customer care and to delimit its current scope. The exercise complements academic literature, which does not include a theoretical analysis of the technology for client service. Li et al. (2020) confirm that research on artificial intelligence for customer service is scarce.

The analysis above on the definition of AI is complemented by the definition of social media customer care. Such field represents the application of the technology in the thesis. Hazée et al. (2021) gather different academic perspectives and describe it as the interaction with private clients in online platforms to provide support and answer messages. This task is independent from consumer status and purchasing power. It results in the development of customer and brand equity.

Building on these insights about artificial intelligence and social media client support, the thesis defines AI as follows.

Artificial intelligence is a rational agent capable of understanding social media support requests initiated by individual customers and proposing favoured solutions through imitation of human behaviour and communication.

Further delimitation of AI in social media customer care requires its differentiation from statistical and business practices. To start with, most of the applications of the technology in social media concern the field of machine learning. This entails a set of algorithms that can

autonomously identify patterns of information and use the uncovered sequences to predict future requests or solve client issues (Overgoor et al., 2019). In addition, AI for online network client support is not statistical modelling and data mining. The first emphasises casual and explanatory relationships over operational effectiveness and prediction accuracy as per machine learning (Agrawal et al., 2018). It requires the brand to grasp through the relation between a variable and the output to a specific error (Overgoor et al., 2019). In contrast, AI is used to make predictions and automate replies without relying on assumptions or rule-based coding (Varian, 2014). The second refers to identification of knowledge and patterns from databases (Shmueli et al., 2017). Therefore, data mining is merely a component of artificial intelligence in customer care.

AI in social media client support functions through unstructured data, i.e. unstandardised and unorganised information; examples include blogposts, reviews, tweets or audio files. Information is then analysed via two main processes: problem solving and reasoning. The former entails the identification of the best solution for a goal, such as an individual complaint on network platforms. The process is twofold. An algorithm can either detect a single sufficient answer to an issue or evaluate alternative solutions that are equally satisfying (Tecuci, 2012). The latter utilises logic to generate conclusions from client observations. It can be carried out through a deductive approach if a customer has enough hypothesis on the cause of the issue or inductive if a customer provides general observations (Pecora, 2014).

The output of AI in social media customer care is natural language generation: creation of complete conversation narratives (Paschen et al., 2020). The transformation of data into human-readable text occurs in five different stages: first, artificial intelligence detects the information that is relevant for service support in the customer's text; second, patterns are detected and data is provided a context; third, data is organised to create a narrative structure; fourth, words and sentences are aggregated based on the relevance for the context; fifth, the output is validated according to syntax, morphology, and orthography (Dilmegani, 2022).

Though academic and business literature on AI applications in social media customer support is limited, a number of examples are derivable from client service research. Chatbots are conversational agents that enable communication via natural language processing and deliver texts to consumers (Araujo, 2018). These tools are often used to extract information from databases and resolve complaints directing the individual to a department or service (Balkhi, 2022). The reader should note that brands can opt for non-AI-driven chatbots, which display minimal intelligence by following pre-programmed paths of questions and solutions (Tuzovic et al., 2018). Further applications of AI in social media customer care are utilised as support

functions to chatbots. To start with, sentiment analysis is a tool to detect the overall mood of the client and perceive the changes in tone of a conversation (Dilmegani, 2022). Then, automated routing allows to forward requests and messages to the most effective brand employee or social network page in a timely manner (Freshworks, 2019). For instance, a client could pose an enquiry on privacy policy to an organisation via its Twitter account. The issue can then be promptly sent to the communication department. Other applications are prioritisation, i.e. artificial intelligence can scan a text to recognise what an issue entails and how severe it is for the customer or measure and deviate actions to those with the longest wait time (Forbes, 2021), and social listening, i.e. the identification of service requests by individuals who have not directly contacted the brand. This can be triggered on social platforms by isolation of key phrases or words, including help, assistance, out of service (Freshworks, 2019).

Integrative Framework of AI in Social Media Customer Care

This section of the thesis shifts attention to academic literature on artificial intelligence and social media customer care. 7 relevant research papers have been identified. The study integrates such prior academic literature into two main categories: design (conceptual and technical), consumer behaviour (emotional and rational). The reason is that these categories incorporate recurrent themes of study; in fact, design is analysed in four papers, the remaining topic is described in three papers. The former have a clear predominance in literature. Design elements suggest how artificial intelligence should be structured and what building processes should be followed. Within the scope of the thesis, this research theme is defined as technocratic analysis. Consumer behaviour is related to the analysis of client's actions and reactions during conversation with artificial intelligence. This theme is referred to as customer view.

The framework above result in three major outcomes, namely positive word-of-mouth, client satisfaction or dissatisfaction. For example, a wrongful interpretation of tone (consumer behaviour) could lead to a rejection of answer from a brand. In the following section, the thesis summarises the key insights from research, as displayed in Table 2, and provides best practices to reach customer expectations.

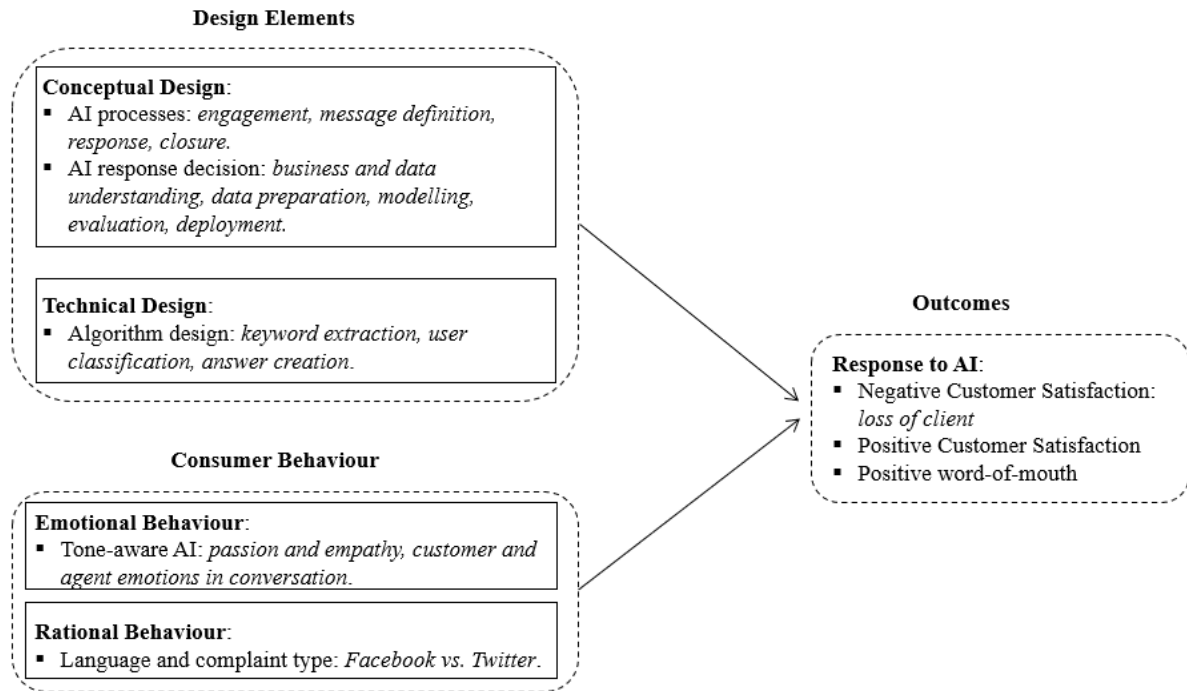


Table 2. Integrative Framework of AI in Social Media Customer Care

The analysis of design elements is twofold: conceptual and technical. The former concerns the proposition of a model that ensures effective and efficient responses to consumer requests (Ghouri et al., 2022). The latter relates to collecting unstructured data and identifying the optimal machine learning algorithm for the data itself (Jimenez-Marquez et al. 2019). This is the predominant field of research for AI in social media customer care.

Ghouri et al. (2022) propose detailed processes that can be implemented through routine for AI in social media customer care. Processes are sets of principals describing individual and organisational actions, including communication frequency, task plans, decision-making methodologies, strategy implementation. Routines are described as repeated, identifiable sequences of interdependent actions whose objective is to provide operational stability. The authors develop a conceptual design model in four processes. First, clients operate in social media platforms. If a contact with a brand's social media page is not established, artificial intelligence does not operate. In contrast, if a client engages with a brand, artificial intelligence filters the requests and decides if the engagement should proceed to the second stage. The authors have found that the intervention of the technology is deemed acceptable by a majority of customers. The reason is that it is perceived as simple to utilise for small tasks and readily available for urgent requests of support. Second, the algorithm defines the type of message received and decides if engagement is necessary. In fact, consumers interact on social media to share experiences of a product or service, validate their feelings and beliefs, gather further

information (Felix et al., 2017). According to Ghouri et al. (2022), these interactions can be divided into five actionable types of messages, which are recognised through routine: acknowledgement (shows appreciation or gratitude for a product or service), complaint (shows criticism as a consequence of malfunction and low quality, unprofessional service, failure to maintain promises), question (presents a matter that necessitates resolution or discussion), rejection (refusal of product or service) and suggestion (presentation of an opinion concerning an offering). Third, artificial intelligence defines the response and the necessity for further support from a human agent if clients are unable to solve their issue via technology algorithms. Fourth, closure of engagement occurs when the user receives a reply from AI. If this results in further observations or questions, the technology can restart evaluation from the first process. The reason is that the second interaction presents a high probability of being different from the first (Ghouri et al., 2022).

Another conceptual design is proposed by Overgoor et al. (2019). The authors suggest a framework to define which customers should receive a reply following a request for client service on social media. In detail, brands should start by defining business objectives and relative customer personas, i.e. geographical area of sale, potential lifetime value, potential for positive satisfaction and word-of-mouth. Then, technology accesses public and required information about a user following receipt of a message. This includes profile and behavioural data. The former refers to number of posts, followers and followees; the latter refers to the range of activities conducted on network platforms. Therefore, artificial intelligence formats the collected data into time series on the user's posts in the previous two hours. The next stage for the brand is to develop a model to classify users based on its business objectives. Finally, the model is tested and deployed by integrating it into customer service systems.

Overgoor et al. (2019) complement the above conceptual design through technical elements. They adopt a traditional logistic model for the classification of profile information and casual state models for behaviour information. Then, they apply K-nearest neighbour method to identify the appropriate class for the customer.

Further technical design elements are analysed by Ozonat et al. (2012). In fact, the researchers define statistical methodologies to extract keywords from social media posts to facilitate the creation of relevant answers. To start with, they reject traditional keyword extraction via tfidf method, which defines the central term of a text by detecting its frequency compared to the repository. The motive is that publications on network platforms usually include limited sentences and number of words. Hence, the authors suggest an alternative approach: create a vector of fundamental words in the repository and generate a binary features vector for each

customer request. If i in the repository appears in a post, i is assigned feature vector 1 and if it does not appear, it is assigned feature vector 0. Keywords are generated through term co-occurrence. It entails the identification of a semantic relation between a given word in a post and another frequent word in the repository. This is computed through the summation of the frequency for the co-occurrence between a term in the post and a frequent word minus the number of times the word occurs and the probability of the frequent word, divided by the number of times the word in the post and frequent word occur together and by the probability of the frequent word. The authors also suggest clustering frequent words based on two conditions: multiple co-occurrence and similar distribution of co-occurrence with other terms. Ozonat et al. (2012) then use a Gauss mixture vector quantisation to design a hierarchical clustering algorithm and reduce the probability of error in keyword extraction.

A third technical design solution is studied by Xu et al. (2017). The underlying assumption of their model is that conversation on online networks entails mapping one set of words in the support request to another set of words in the reply. The system is formed by two long short-term memory neural networks: the encoder maps a variable-length input set to a fixed-length vector, the decoder maps the vector to a variable-length output set (Xu et al., 2017). Note that words in a service message cannot be utilised as inputs in the long short-term memory networks. Therefore, the authors adopt a word embedding method: word2vec neural language models. This enables to classify a term for its nuances compared to others, thus creating a continuous spectrum of tones and interpretations for a specific meaning. This statistical solution was demonstrated to outperform information retrieval baselines and perform consistently with human agents in terms of appropriateness, empathy and helpfulness.

Academic literature about artificial intelligence in social media customer care also reasons on consumer behaviour. The analysis is structured into two categories: emotional and rational. The first refers to recognition of customer sentiment (Balkhi, 2022); the second to provision of information that could support customers in solving their issues (Xu et al., 2017).

Hu et al. (2018) have detected eight emotional tones in customer service for online platforms via literature review: anxiety, frustration, impoliteness, passion, politeness, sadness, satisfaction and empathy. A subsequent experiment demonstrated that the most encountered tones were politeness and sadness. Consumers also often perceived passion and empathy in conversation. Note that changes in these two sentiments for customers resulted from the tones used by agents in social media customer care (Hu et al., 2018). The analysis of anxiety, politeness, sadness and frustration revealed similar, though less significant, results. In this context, it is clear that sentiments are central to providing customer satisfaction when

interacting with AI. To ensure that artificial intelligence is capable of detecting tone, the authors opted to endow their algorithm with keyword extraction and deep learning techniques, such as modified seq2seq models for language generation. As a result, Hu et al. (2018) demonstrate that artificial intelligence is perceived as more appropriate when passionate response are generated – compared to empathic and neutral replies – and more empathic compared to human agents.

Additional analysis on emotional consumer behaviour is undertaken by Herzig et al. (2016). Their paper developed classifications to detect client emotions on social media support requests and to predict the emotional technique utilised by a human operator or chatbot. Through the application of SVM-HMM dialogue models, the authors demonstrate that satisfactory performance can be reached in the quality of dialogue. In detail, Herzig et al. (2016) identified through research review a set of emotions for customers (confusion, frustration, anger, sadness, happiness, hopefulness, disappointment, gratitude, politeness) and respondent agent (empathy, gratitude, apology, cheerfulness). Then, the authors devised a method to extract dialogue features from service exchanges in social media: integral features represent the topic of dialogue, objective of the respondent agent, turn number; emotional features reflect customer and agent emotions; temporal features indicate response time and day of the week. Herzig et al. (2016) demonstrate that the inclusion of these three elements in the artificial intelligence model improves performance of customer service and that the utilisation of emotional features results in more informative replies.

Agnihotri et al. (2020) have assessed the manner in which chatbots constructed via artificial intelligence and clients interact on complaints in various social media networks. It is the analysis of rational consumer behaviour elements. The researchers point out language differences in messages on Facebook and Twitter: customers utilise Facebook for purposeful complaints as they seek for a solution to their issue, whilst they use Twitter for expressing anger over service malfunctions. In addition, Twitter is preferred for clear, precise observations, typically initiated through posts on existing conversations in the platform. In contrast, users opt for detailed explanations on brand social media pages in Facebook. Thus, responses to immediate support were straightforward on Facebook and often sarcastic on Twitter. Agnihotri et al. (2020) specify that customer care is requested either through personal post on Facebook or Twitter pages or comment on a thread by a sponsoring brand. Note that customers tend to complain or post negative texts under advertised or promotional publications. The cause of complaints included product quality, delivery, handling, after-sales

service, return, other issues. The study has also revealed that pre-defined statements stated by autobots based on artificial intelligence seem insufficient to resolve customer complaints.

Research Propositions for Academia and Business Practices

The thesis has presented unambiguous literature on design and client behaviour elements, as demonstrated in Table 2. The current section aims to point out the remaining open questions on artificial intelligence in social media customer care. In particular, it is structured into two segments. The first depicts future research directions identified by the 7 papers described above. The second highlights other potential fields of study in light of the literature review developed by the thesis.

According to Ghouri et al. (2022), future work should demonstrate their findings in variegated sectors and firm characteristics – with large sample sizes – as the authors solely focused on well-established firms, which tend to be more structured. Further validity can be achieved by understanding the discrepancies between the performance preceding and succeeding the implementation of their methodology. These suggestions reflect those of Agnihotri et al. (2020). They advise to expand their findings to different industries and platforms, thus taking into consideration the role of culture. Moreover, they suggest comparing via experiments social media with traditional channels. Xu et al. (2017) propose five future fields of study arising from their work. To start with, they point out that social media is an emotional, rather than informational, customer service channel. This due to higher restrictions from public visibility of comments. Therefore, literature could examine the relationship between clients' motivations and emotional response on social media. The authors also ask what the optimal collaboration solution between AI and human agents is to provide customers with the best service. In this context, they also propose a long-term study on the impact of chatbots on customer perceptions of brands. Hu et al. (2018) suggest two directions of research. The first concerns the effects of agent tones at a finer granularity and its impact on customer engagement. The second recommends the extension of their model to include brand- and style-aware chatbots. Herzig et al. (2016) also devise two implications for academic literature. They affirm the necessity to apply their predicted emotional technique to new dialogues and determine the effect on real-life scenarios. In addition, they propose to distinguish between conversations with positive and negative outcomes. This entails considering the role of customer satisfaction.

Within the context of this thesis, other open questions arise from the literature review. To start with, a systematic analysis of academic and business articles is required to highlight other potential themes. Then, a theoretical distinction between non-AI driven chatbots and AI-driven

chatbots should be performed within the sphere of customer service on network platforms. Yet, the most considerable learning is that current knowledge on the abovementioned field is highly focused on technocratic analysis of AI. In fact, nearly the totality of studies reflect this statement. Whereas some authors clearly aim to focus on identifying relevant statistical solutions to improve efficiency of AI, others claim to analyse customer behaviour but frequently adopt a technical approach. It is clear that defining a solution to build empathic and precise algorithms is just a first step in guaranteeing customer service quality. The second requirement is to consider customer perspectives. Take, for instance, the possibility that AI could be as effective in supporting a client as a human operator but the client itself might be reluctant to the use technology. Further examples of future work in relation to consumers are the effect of contextual elements on opinions about AI, role of brand tones, feelings and quality perception of automated replies.

Further research is also driven by business necessities. Corporations should ensure positive interactions with their customers as this ensures higher economic performance (O'Brien, 2021). Therefore, it is worth analysis user experiences and perspectives on artificial intelligence in social media customer service.

In light of the findings above, this thesis proposes to analyse customer perspectives and perceptions and deliver client-oriented research results on AI in social media customer care. Table 3 shows the differentiating factors between the current thesis and previous academic literature.

Research Paper	Theory Presented	Findings	Methodology	Research Elements
Ghouri et al. (2022)	To provide a structure for artificial intelligence in social media customer care, focusing on processes and routines	The paper has defined a set of principals describing individual and organisational actions: client engagement, definition of type of message, creation of response, closure of engagement	Theoretical Research	Conceptual
Overgoor et al. (2019)	To propose a framework to define which customers should receive a reply following a request for customer service on social media	The paper suggests a process that involves the definition of business objectives, access to the client's public information, development and deployment of AI model	Theoretical Research	Conceptual
Overgoor et al. (2019)	To define the statistical process for classification of profile information and user prioritisation	The paper adopts a traditional logistic model for classification of information and applies K-nearest neighbour to identify appropriate classes	Statistical Research	Technocratic
Ozonat et al. (2012)	To define statistical methodologies as to extract keywords from social media posts and facilitate creation of relevant answers	The paper creates a vector of fundamental words in the repository and generates a binary features vector for each customer request	Statistical Research	Technocratic
Xu et al. (2017)	To map one set of words in the support request to another set of words in the reply	The paper suggests to build two long short-term memory neural networks and wrd2vec neural language models	Statistical Research	Technocratic
Present thesis	To define the impact of artificial intelligence on social media customer care focusing on client perspective	The thesis investigates AI agent disclosure and brand image as determinants of customer satisfaction in social media support requests	Business Research	Consumer view

Table 3. Extraction Table, State of the Art for Academic and Business Literature

Exploratory Qualitative Study: Customer Perspectives on AI in SMCC

The literature review above concluded that research on AI in social media customer care has focused on the technical analysis of the software. To expand the field of study, this thesis has conducted a qualitative analysis through fourteen interviews on a sample of participants. The exercise is appropriate as it allows to explore respondents' perceptions and propose a novel research focus for academia. In addition, it enables to reduce the complexity of client feelings and reactions by defining key variables of research (Sauro, 2015).

Research Design

Data Collection and Sample Characteristics

This study uses qualitative, semi-directed, in-depth interviews to understand customers' perspective about artificial intelligence in social media customer care. The sampling design adopted is maximum variation, which allows to identify patterns across different cases and derive significance from heterogeneity (Palinkas et al, 2016). This method is justified as the purpose of this study is to explore customer perspectives in the market without a detailed focus on behaviour or contextual characteristics. In this context, the population selected for the thesis is the European Union. The participants to the meetings were selected based on personal contacts of the author, such as friends, family, acquaintances. The logical criteria utilised for the creation of the sample were age, gender, education level and job employment. Researchers have demonstrated that age has a significant impact on the experience of technology. Czaja et al. (2006) demonstrated that use of innovative products diminishes as seniority increases and is associated with feelings of anxiety and inefficiency for older generations. Moreover, physical, sensory and cognitive impediments arising with age partially explain the reluctance to adopt technology as lifetime raises (Melenhorst et al., 2006). Bain et al. (2006) demonstrate that there is a significant bias in technology interests and use across genders, as a result computer skill might diverge between females and males. Riddell et al. (2012) analysed that increases in education level correspond to raises in the use of technologies. This is specifically true as higher knowledge allows to use software for more complex tasks. Finally, the ideological principle of technological unemployment posits that job losses are structurally caused by innovation. Hence, the employment level of the interviewee might affect its experience and perception of artificial intelligence.

Building on this theoretical background, the sample of interviewees constitutes of five women and nine men, eight secondary or lower education and six tertiary education, nine employed

and five unemployed. Greater emphasis was placed on younger generations as they are logically expected to be more prone to utilise social media and innovative solutions for customer service. Outlier populations, i.e. children and elderly, were not considered for the scope of the thesis. In fact, the former group are tutored by their parents and are not expected to contact a corporation, the latter rarely have the skills and knowledge for utilising complex technology. The number of interviews was limited to fourteen as saturation of answers was achieved.

Research execution was developed in two steps. First, the author contacted around twenty connections from its network that reflected the characteristics mentioned above. This first reach out enabled to briefly describe the scope of the interview and request potential availability for a period of two to three weeks. This contact frequently occurred through text message or telephone call. Once a date for the interview was defined, the author prepared for the meeting. The interview guide and literature review were consulted in multiple occasions to ensure a satisfactory knowledge of the topic and research question. Then, the interview was conducted. Most of the interactions occurred at dinner time or late in the evening to accommodate working and studying schedules. In addition, the meetings took place via phone calls or virtual webcam. This was necessary to ensure the reach of different geographies across the European Union. The duration of the interviews spanned between 25 to 50 minutes, and the average was around 35.

The quality of data was assured through accurate and precise transcripts. The interviews were recorded on a digital device. As the interviews were not conducted in English, each word was translated from the author, who is proficient in both the speaking and thesis language. Personal conversations were omitted due to privacy reasons.

Interview Guide

An interview guide was developed to facilitate communication between the author and the volunteers. This exercise was completed through a structured process. The author defined the scope of the interview by listing the research question and complementing it with the conclusions from the literature review, i.e. the necessity to further explore customer experience of artificial intelligence in social media customer care. This resulted in a list of three fields of knowledge, namely customer service, network platforms and AI. These were then arranged through a funnel approach into a set of questions. In other words, the interview started from a general issue about customer service and then proceeded to a more detailed conversation on social media and artificial intelligence. The objective is twofold. First, this approach allows to

introduce service quality in client support as defined in the first section of the literature review. This includes an investigation on reliability, responsiveness and empathy. Second, it allows the interviewee to ease into the conversation and feel comfortable with the dynamic imposed by the author. Table 4 displays the results of this exercise.

Interview Section	Question or Proposition Order	Interviewer's Question or Proposition
Introduction		1 Hello, I am Riccardo Casarin, Master Student in Business Engineering at UCLouvain. I have organised this interview within the context of my thesis. This meeting is completely voluntary and it can terminate at any time you deem relevant or appropriate. 2 For scientific reasons, I will be recording this interview. The audio will not be made public and is kept by myself only. Any reference to our conversation will be purely descriptive and anonymised. 3 Are you ok with the conditions I have proposed?
Opening Question: Customer Service Experience		1 Could you explain your last experience with customer service? 2 What was the goal of your contact with customer service? 3 How did you feel during your last aid request to a brand? 4 Could you share if you were treated with empathy, if support was prompt, if information provided was accurate and useful?
Social Media as a Customer Service Channel		1 What is your experience of customer service via social media? 2 What have you found helpful or troubling in your exchanges?
AI as an Intermediate in Customer Service on Social Media		1 In the field of customer service, artificial intelligence is delivered to customers via chatbots and automated replies. 2 How would you perceive a response of AI on social media when requesting support for a product or service? 3 When would the support of AI be more appropriate and more challenging for your requests on social media?

Table 4. Interview Guide: Social Media Customer Care and AI

The questions in Table 4 were developed based on a set of four principles. To start with, open-ended enquiries were selected as they allow interviewees to describe personal experiences at their own terms and to collect in-depth information according to each customer's priorities. Moreover, questions aimed to be clear, i.e. simple and short. Any jargon or technical term that appeared during a meeting was explained by the interviewer. The objective is to avoid problems in the use of terminology; for example, a word could be interpreted in a divergent manner between participants to the study. In addition, each question represents one single point of interest for the present study. Finally, direct questions were preferred as they enable to steer the conversation more easily compared to indirect or structuring queries.

Before asking questions, the ground rules for completing the meeting were specified. It was detailed that the interview was completely voluntary and could terminate whenever the volunteer deemed relevant, that the interview was being recorded and transcribed for the

benefit of research. In addition, the volunteer was made aware that any reference to its responses would have been anonymised and generalised. Only after consent was given, the interview took place.

As anticipated above, the interview followed the structure of the literature review. It commences by introducing a neutral open question. The questions ask what was the last instance in which the volunteer contacted a company's customer service. In addition, they clarify what circumstances and feelings pervaded the interaction with the support service. Then, the interview shifted attention towards the topic of social media customer care. This lays the background condition for the last set of questions on AI. It prepares the interviewee to consider its answers within the realm of social networks. In detail, the author asked if the participant had ever contacted an organisation on social media to solve an issue with a product or service. A second follow-up question was asked concerning what was considered helpful and challenging in the use of the mentioned communication channel. The final set of queries focuses on the role of artificial intelligence and tries to analyse the experience of the client with the technology. They ask what the perception in case of disclosure of the technology is and when it would be more accommodating or opposing. Note that the objective of this structure is to reduce social desirability bias. In fact, respondents might tend to display enthusiasm for technology innovation. Therefore, introducing AI towards the end of the conversation might reduce propensity to display positive opinions.

A final remark concerns the flexible use of the interview guide. The author frequently clarified the definition of artificial intelligence in social media customer care and, on one occasion, defined what client support consists of in social networks. If the interviewee was not aware of the field of study or technology, the author asked to imagine a fictional experience and describe potential feelings or perceptions. It should be noted that all participants to the study use frequently social networks – even if not specified in the interview transcript – and therefore were judged capable of providing reliable answers. Finally, it should be noted that customer service and customer care were not distinguished during the interviews as to avoid confusing participants.

Data Analysis Approach

To explore the results of the qualitative study, the thesis conducts a thematic analysis. A theme identifies a relevant element in the data which is related to the research question and represents a pattern within the responses collected (Braun et al., 2008). As a rule of thumb, the selection

of the theme was dependent on its importance relative to the research question: what customer perspectives on artificial intelligence in social media customer care are.

As mentioned above, data analysis has been conducted through a rich thematic description of the complete data set. The ambition is to provide the reader with an in-depth understanding of the predominant themes (Braun et al., 2008). This solution has been adopted as it enables to investigate and expand academic knowledge in a field of study which is under-researched. In this context, the thesis adopts an inductive approach to analysis. Therefore, the detected themes are a direct result of the data gathered (Patton, 1990). The advantage is that the identified themes are not related to the interest of the author or other pre-existing codes, but rather reflect the most prominent customer perspectives. To further ensure that the themes are applicable to future analysis, semantic and realist approaches are adopted. The former entails that the themes respond to explicit or surface meaning. No interpretation goes beyond what the interviewees declared. Hence, the analysis is descriptive and simply organises the patterns of the data. The latter assumes a unilateral relationship between significance and language.

The process of analysis follows the phases suggested Braun et al. (2008). During the transcription of the interviews, the author noted down potential ideas and schemes. An identity number (ID) was assigned to each interviewee to facilitate note taking. Then, it coded interesting features in the participants responses across the whole data set. In detail, a list was created containing the main perspective or experience described by the respondent for each question. Then, potential themes were identified and assigned to the responses collected. This facilitated the identification of relevant extracts to include in the analysis.

Research Results

This segment proposes a summary of the themes identified in the exploratory qualitative analysis and suggests their relationship. To reduce complexity, a conceptual framework is proposed indicating variables derived from the findings, moderator effects and outcomes. This is displayed in Table 5.

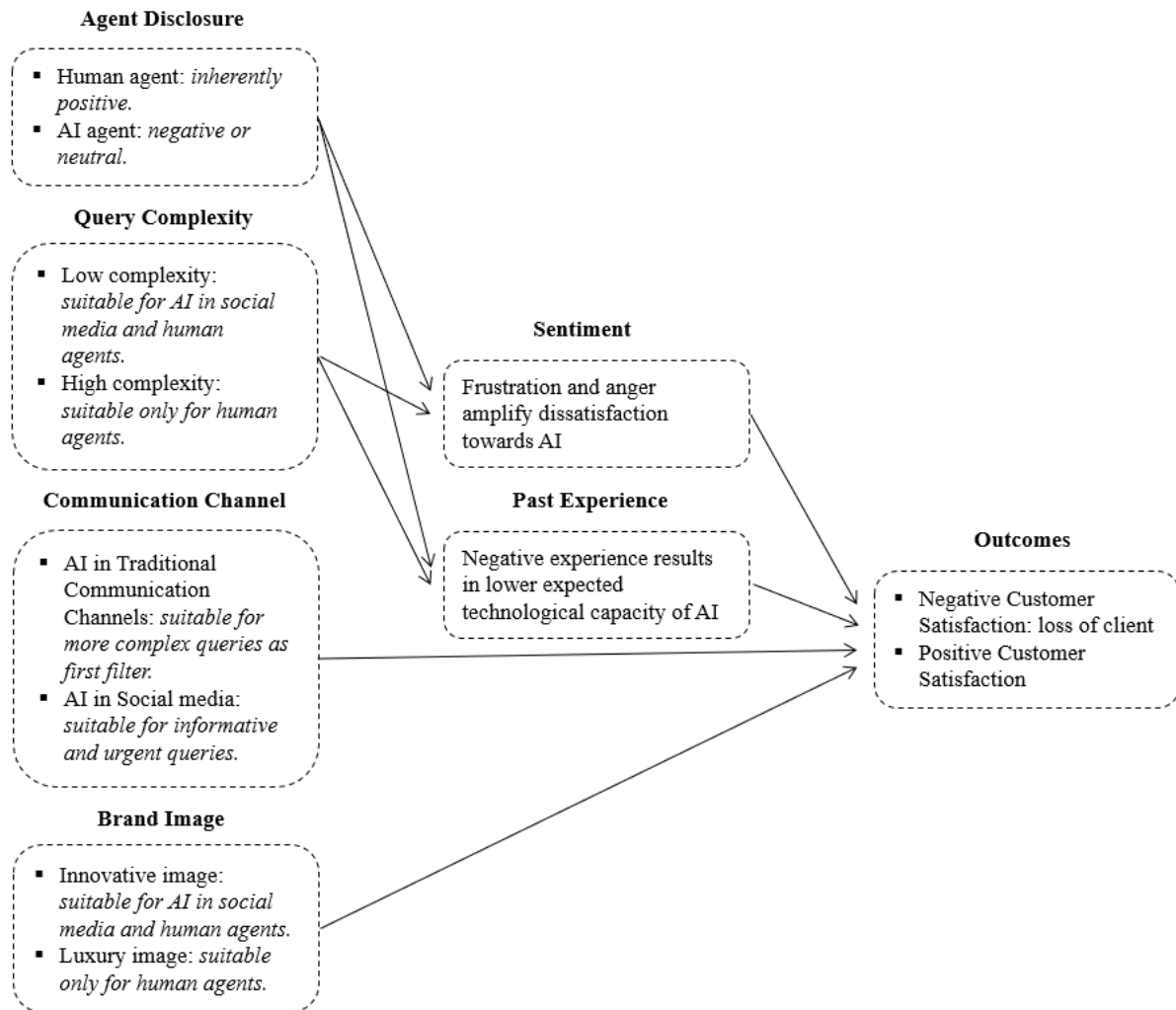


Table 5. Conceptual Framework: Customer Perspective for AI in SMCC

The central themes that emerge from the interviews are four: agent's nature disclosure, complexity of query, communication channel and brand image. The following paragraphs will detail each theme and propose relevant extracts to support findings.

The theme of agent's nature disclosure during customer service requests on social media has emerged across answers from participants in the interviews. Two contrasting levels of analysis were identified: the nature of the support is divided between human and artificial intelligence; human agents are perceived as inherently positive, whilst AI agents are reckoned to be inherently negative or neutral. The distinction between human and artificial intelligence was proposed by volunteer 1 at the stage of the opening customer service question.

ID 1: *At start I was answered by a chatbot which proposed general questions to understand the nature of my enquiry. As I could not solve the issue, I was connected with a human agent.*

The counter position of automated and human replies was reinforced at by all respondents when answering the questions on AI as intermediate in customer service within social media. A number of respondents explain that understanding or being communicated they are aided by AI is inherently negative. In fact, one respondent demonstrated complete refusal of AI as solution to his issues.

ID 3: *I would not like the use of AI. I think a human agent would be easier to deal with. It would enable to understand the issue quickly. I would never perceive artificial intelligence as useful. I have only solved issues with human agents. I do not think the technology is advanced enough.*

ID 4: *I reckon that direct human interactions are more efficient and empathic. I can explain the issue in more detail, and I believe that a human agent can understand the problem at stake more easily. I also prefer websites because interactions are longer, and I feel I can make follow-up questions.*

ID 9: *I would not appreciate it. Why is the company using AI? I have a problem and the firm replies through an algorithm, I do not understand it.*

ID 14: *My perception is negative. Up to now, I have never found an AI that was developed enough to solve a complex issue. I feel like AI is suitable just for standard answers.*

Furthermore, the participants that proposed a negative attitude towards AI agent disclosure added their reaction stems from the perception that the use of the technology is a lack of attention towards the problem they present to the company.

ID 4: *If I were to contact a company on social media, I would perceive an automated reply very negatively. I would form the assumption that the company is not taking my query seriously.*

ID 5: *I would perceive it as quick fix from the company. I would assume the company does not care about the client.*

In contrast, some participants explained that they have a neutral stance towards artificial intelligence as their only objective is to solve the query posed to the organisation as efficiently and timely as possible.

ID 2: *From a general perspective, AI does not bother me. My priority is always to solve a problem as quickly as possible.*

ID 3: *I do not have any distinction between AI or a human agent. I only care that the issue for which I am contacting the firm is resolved.*

ID 7: *I really do not care if I receive a response from AI or a human agent on social media. Solving the issue is the only relevant matter for me.*

Human support has been identified as the other variable in the theme of agent disclosure. Almost the entirety of the data set portrays human answers as more appealing and a benchmark of comparison for technology solutions.

ID 3: *I would not like the use of AI. I think a human agent would be easier to deal with. It would enable to understand the issue quickly.*

ID 6: *AI has similar limits to what I just described before: it does not give enough value compared to a human support.*

ID 10: *AI is not a solution. A person is more flexible and can understand the issue very easily. It is just more efficient.*

A second theme introduced through the interviews is the complexity of the queries posed to the organisation. In the qualitative research, complexity appeared to be defined in two manners: complexity of request and complexity of interaction. The former refers to the expected level of creativity required to solve an issue.

ID 4: *Complex issues that involve creative solutions or considering multiple options would be challenging for AI.*

ID 10: *I feel AI on social media [...] would not be suitable for complex issues.*

The latter to the expected number of exchanges or messages required to solve the issue.

ID 8: *I believe it would be very difficult for AI to respond to various questions effectively on social media. Just think what would happen if another a customer interferes in the conversation, how would that pan out?*

For the purpose of this study, complexity is considered as a unique theme that comprehends both definitions. A majority of participants in the study highlight that AI in social media is best suited for quick, recurrent questions which can be answered with certainty from the algorithm. Therefore, artificial intelligence would be perceived as helpful for low complexity queries. In contrast, human agents would be preferred for creative, out-of-the-box thinking. This is clearly demonstrated across demographics.

ID 1: *I believe AI is a first aid solution and could be suitable to deliver a precise piece of information on which a brand possesses enough data and standard answers. It is a quick, efficient system. It will be more challenging for complex issues.*

ID 6: *Chatbots might be helpful, but I believe this is the case only for standard and frequent responses in which questions are pretty simple and straight forward.*

These first two themes were moderated by two variables, namely sentiment and past experiences. A number of participants to the study have shown that frustration or complete closure towards artificial intelligence is capable of negatively amplifying their perception and satisfaction towards customer service. This has considerable impact as some customers are willing to disrupt their relationship with a company, which could cause negative word-of-mouth, as demonstrated by interviewee 7, who declares: *“Just imagine what would be the effect of my contacts on Facebook seeing my complaint. I doubt their perception of the firm would not change”*. In addition, participant 4 disclosed that past experience has developed a negative bias towards artificial intelligence in customer service: *“The reason I have formed this opinion is that my experience with bots is not always positive. It has occurred that bots would not be able to identify the issue at stake even for simple and straightforward questions”*.

The third theme identified is communication channel. In fact, artificial intelligence is described as suitable for different motivations according to the medium through which the client contacts the organisation. Within a website or online chat, AI is considered a positive first support. It is a solution to quickly identify the issue at stake and support the intervention of a human agent.

ID 1: *[AI] is a first filter for customer service, and it provides quick solutions.*

Within the context of social media, artificial intelligence is considered useful as it allows to receive immediate replies. This fits the participant's objective in network platforms. Service requests in this channel mostly occur as a last resources or emergency. Moreover, social media prioritises straight-to-the-point conversations. Thus, a quick reply would placate, though temporarily, the pain of the customer. No respondent has considered empathy as a factor in judging the relevance of AI in either communication solutions.

ID 2: *Given that I believe social media is a last resource, in such circumstances receiving an answer [from AI] would be positive.*

ID 7: *I believe that it would be interesting to receive a response from AI because it would offer a reply in very limited time. This would help the firm's reputation and satisfy at least momentarily the client.*

The fourth variable identified through the qualitative analysis is brand image. It appears that innovative, tech-oriented brands would be perceived as more suitable to adopt artificial intelligence agents in social media. In contrast, customers might be offset if established or luxury brands would adopt a similar tool without building awareness beforehand.

ID 2: If the company is very active on social media, then probably the use of AI would be very useful, and I would welcome the solution.

ID 7: I think it would be appropriate for companies that are characterised by early adopter customers. I believe these clients have less bias towards the technology. I guess established or luxury brands might struggle in convincing their customers that AI can help with their problem.

A final remark from the qualitative analysis concerns the literature review. The interviews highlighted that service quality depends on the responsiveness and reliability of support as well as the empathy displayed by a human or automated agent. The lack of these three variables caused dissatisfaction in various volunteers, leading two to publicly affirm they are no longer willing to purchase from a company. In practice, negative feedback about customer care was frequently linked to miscommunication or missed alignment between client ambitions and corporate policies. In the former case, various respondents highlighted that the firm's agent was unable to understand the complaint or incapable to signal a party skilled enough to solve the issue presented. In the latter case, some volunteers expected to receive reimbursements or renewal of contracts but were not able to reach their objective due to restraining corporate guidelines. However, the majority of customers signalled a positive, effective experience with customer service. The overall sentiment was that empathy and responsiveness were guaranteed.

Hypothesis Development

Building on the literature review concerning customer satisfaction and the exploratory qualitative study findings, this section develops the research hypothesis for the empirical quantitative study. It considers design elements which have not been researched sufficiently and represent a priority for current business operations, namely AI agent disclosure. In fact, a number of organisations are investigating the use of artificial intelligence in customer service (Huang et al., 2018) and are researching if customers should be informed of the technological nature of a response (Hazée, 2021). Though 80 percent of brands declare to use AI to provide client support (Oracle, 2016), not all companies declare if such aid is provided by a human agent or a chatbot. In addition, companies are pressured by policy makers to adopt a definitive stance on agent disclosure. For example, the State of California passed a law (California's Bot Disclosure Law – SB 1001) which obliges organisations to declare if clients are interacting with an algorithm or an employee. This situation makes an investigation of AI webcare agent disclosure both timely and relevant.

H₁: Disclosure of AI vs. human agent in the response to a customer service enquiry on social media negatively influences customer satisfaction.

Lin et al. (2020) explain that a number of factors impact consumers' attitude towards artificial intelligence, including the added value delivered by the use of the technology compared to a human interaction. Therefore, if interviewees had negative past experiences with chatbots in corporate websites, they could develop a bias towards human interactions on social media. This is confirmed by stereotyping theory. Fiske et al. (2021) suggest that customers unconsciously define the reliability of disclosed artificial intelligence less satisfactorily than human agents. The reason is that algorithms have yet to reach a satisfactory level of support independent of the nature of the client's question. This has been also suggested by the exploratory qualitative analysis. In fact, respondents judged human agents more effective in overall problem solving. Moreover, several participants highlighted a negative bias towards artificial intelligence and one declared a refusal to use the technology for customer service enquiries.

ID 4: If I were to contact a company on social media, I would perceive an automated reply very negatively.

ID 3: *I would never perceive artificial intelligence as useful. I have only solved issues with human agents. I do not think the technology is advanced enough.*

The negative impact of AI disclosure is confirmed by Li et al. (2020). The authors identified that nearly 30 percent of clients using support services is resistant or strongly resistant to technological aid. According to the qualitative research, the remaining part of customers do not have a positive perception of AI, rather their stance is neutral. Their sole objective is to solve the issue at stake as fast as possible.

ID 2: *I do not have any distinction between AI or a human agent. I only care that the issue for which I am contacting the firm is resolved.*

H₂: *The negative impact of the disclosure of an AI agent on satisfaction is mitigated (accentuated) if the brand is innovative (sophisticated).*

The perception of AI-based customer service on social media could also be impacted by the organisation's personality. Clients of sophisticated brands, i.e. usually identified as elegant and prestigious, could react negatively to a response from artificial intelligence after a request for aid (Hazée et al., 2021). Prestigious brands typically attract clients from wealthier social classes who expect help services to go the extra mile to ensure a responsive and effortless solution to their issues (Muusers, n.d.). In line with signalling theory (Connelly et al., 2011), an answer from a human agent could signal that the organisation is eager to delight its clients.

ID 7: *I guess established or luxury brands might struggle in convincing their customers that AI can help with their problem. It would probably require a considerable awareness or marketing campaign.*

In contrast, innovative or exciting brands are accepted to provide innovative solutions to appease their customers (Barlow, 2016). Building effective AI support service might be a signal that brands aim to appease their clients through up-to-date solutions. In fact, an interviewee highlighted that a customer base of early adopters could perceive AI as satisfactory.

ID 1: *I also think that AI would be more appropriate for tech-oriented brands as their clients would be even happier to interact with AI.*

Empirical Quantitative Analysis: AI Agent Disclosure and Brand Image

In line with the hypothesis development above, this section of the thesis tests the role of AI agent disclosure and brand image within the context of social media customer care. To achieve this objective, it has conducted an experimentation. This consists of the collection of 278 respondent's answers via an online survey. The exercise is relevant as to confirm via statistical analysis the opinions and behaviours identified in the exploratory qualitative study (QuestionPro, 2022).

Research Design

Research Method

The study has questioned four groups of individuals each representing a set of two different variables. This entails customers experiencing either AI or human agent disclosure and innovative or sophisticated brand personalities. Similar to previous academic literature (Van Vaerenbergh et al., 2013), the research has adopted a scenario-based experiment to test the hypothesis from the exploratory qualitative analysis. The reason for such selection is that scenarios are frequently adopted for client satisfaction research (Hague et al., 2022) and remove the difficulties linked to observation or representation of experiments in real life (Bitner, 1990). In addition, scenarios eliminate the biases linked to memory retrieval typical of recall-based investigations (Smith et al., 1999).

Volunteers are questioned through a structured approach. To start with, the survey commences with a description of the author and the context within which the investigation takes place. Moreover, the respondents are presented with the conditions for participation, including anonymity of answers and privacy protection. After the provision of consent to such restrictions, respondents are invited to carefully read a scenario and imagine themselves in the situation. Each scenario starts through the description of the brand image: either up-and-coming, technological or luxurious, well-known. Brand image was conveyed through a description of consumers' typical impressions about the company. This enables the reader to identify with the product and what it stands for (Solomon, 2016). Then, it is declared that the brand has recently released a new product and, in the midst of the hype, the respondent has decided to purchase one. At this point, each reader is informed that such good broke down after a few weeks. To solve the issue, she or he decides to contact the company via social media and an AI or human agent responds. These conversations are demonstrated here for AI – Up-and-coming and technological brand scenario. Further details can be found in the Appendix section.

You write the following post: “@_brandname_ your product is faulty. It just broke down! This is very inconvenient”.

The brand replies to your post: “Hi Customer. I'm sorry about the issue. I'm going to solve this. I would be happy to send you a new shipment of the product, a refund or some different items of your choice. Let me know how I can improve this situation. Thank you for writing! – Kobe, AI customer service agent”

The response from AI or human agent does not solve the issue for the customer. This is intentional as the scope of the research is to verify the impact of disclosure rather than the resolution of the problem at stake. The interaction above was reported on the survey both via an image of a Twitter conversation and in text format. The former served to aid the participant in imagining the scenario. In fact, Agnihotri et al. (2020) demonstrate that Twitter is preferred for quick posts displaying anger. The latter to provide a visual aid in case the posts were not readable.

In addition, the survey presented the privacy agreement, instructions and questions on separate pages to ease comprehension from the volunteers. The questions relative to the scenario were separated from those concerning manipulation and realism. From a practical perspective, responses were collected through Qualtrics and the surveys were distributed via personal messages on social media platforms, including WhatsApp and LinkedIn. To expand the reach of the survey, data was also collected in public spaces by sharing the questions with individuals available for a few minutes. The exercise reached 278 people. This number reflects indications from Hyman et al. (2010), who suggest that every scenario in the customer survey should include between 20 and 100 replies.

Measures and Analysis

The respondents defined their overall satisfaction and repurchase intentions on three questions displaying a seven-point Likert scale. This was adapted from Van Vaerenbergh et al. (2013). Evidence for the use of this scale is also provided by Finstad (2010). The author demonstrated it is more accurate and easier to use compared to five-point or larger Likert scales. It enables to capture a participant's realistic evaluation. The survey asked if the volunteer was satisfied with the customer service experience and the company. Further questions were relative to repurchase intentions and service quality. In addition, the study assesses customer service quality based on three criteria of judgement: poor to excellent, inferior to superior, low standard to high standard. Manipulations and scenario realism are also adapted from Van Vaerenbergh

et al. (2013). In detail, the survey asked the respondent to confirm the key variables assessed, i.e. agent type and brand type, and to state if the scenario was realistic or possible in real life. The first are defined through a two-option multiple choice answer, the second through a seven-point Likert scale.

The analysis of collected information was preceded by a data screening process. To start with, the author imported data on an Excel file and used Power Query to promote the first rows to headers. This enabled to assign to each column a title corresponding to a question in the survey. In addition, a number of columns were eliminated as they were not useful for the analysis, including start date, longitudinal and latitudinal coordinates of the respondent, empty respondent's personal information columns. The column representing the end date was split to separate the day of completion of the survey and eliminate the hour. The final action on Power Query was to change the columns' type to whole number for all the answers which entailed a Likert Scale and the age of the respondents. Moreover, the first four data entries were eliminated as they did not contain any answers. In fact, these were four mock trails to verify that the survey was functioning as desired and was intuitive to utilise. 72 data entries were also eliminated as they contained missing values. In detail, these respondents just completed questions on customer satisfaction, repurchase intentions and service quality. Manipulation checks, scenario realism and personal information were not completed. Therefore, these surveys were not finished. A further data entry was erased from the dataset as one respondent did not provide its consent to the data treatment policy. This left a dataset of 201 responses. In addition, service quality and scenario realism values were modified to reflect the 1 to 7 points in the Likert Scale. The reason for such change was an underlying issue in the downloaded dataset. Moreover, the author created two dummy variables according to the categorical variables declared by the participants and two other dummy variables according to the categorical variables assigned by the randomised scenarios, i.e. AI Assistant vs Human Employee agent and Up-and-coming and technological vs Luxurious, well-known brand. The answers to "I am NOT satisfied with this company" and "In the near future, I will NOT use this company any longer" were inverted in order (from 1 – 7 to 7 – 1) to account for the negative effect of the question. Finally, a column containing respondent IDs was included to facilitate analysis.

The analysis was conducted in Excel and Jamovi. Manipulation checks were verified by creating two contingency tables representing the observed and expected categorical variable answers. The two tables were created to perform dedicated analysis for agent and brand type. The Chi-square test was used to interpret the results. Scenario realism was evaluated by

computing a dependent variable equal to the mean of the answers to the two scenario realism questions. These were then assigned to four experimental groups according to the combination of agent and brand type. One-way ANOVA was utilised to verify the participants' perceptions of the scenarios. The internal reliability analysis was achieved by performing separate two-way ANOVA without replication on the three sets of questions customer satisfaction, repurchase intentions and service quality. This allowed to compute the Cronbach's Alpha through the formula $1 - (MSE/MSR)$. Then, three new variables were created by computing the average response for customer satisfaction, repurchase intention and service quality for each participant. This allowed to perform the Levene test by computing the mean answer for the three variables in all data entries and completing a Residuals Table. A single factor ANOVA enabled to check equality of variances. The final analysis was conducted via Jamovi. A two-way ANOVA enabled to verify the hypotheses declared in the previous section of the thesis. The study assumes $\alpha = 0.05$.

Research Results

This section of the study proposes to evaluate the results of the empirical data collection. It is structured into three segments. First, it proposes summary measures to identify general demographic characteristics of the participants to survey. Second, it conducts manipulation checks with the objective of verifying if respondents perceived, understood and reacted as foreseen to the identification of assigned scenarios (Hoewe, 2017). Third, it tests the hypothesis described in the previous section of the thesis and discusses the findings.

Descriptive statistics on the dataset provide an overview of the respondents. 106 females participated to the survey compared to 92 males, 2 individuals preferred not to declare their gender and 1 identified as non-binary or third gender. The number of participants from the European Union was 186, compared to 13 which answered from other continents. Finally, the absolute count of tertiary or higher education strongly outnumbered those with secondary or lower education, 144 and 39 respectively. The remaining preferred not to say what their education level was. In contrast, employment was evenly distributed: 107 individuals declared to be employed, 64 stated otherwise, 30 opted not to say. Finally, age was strongly left skewed towards younger generations. Though the mean age was 29.5, the median participant was 24 years old and the mode was equal to 23. Non-central position measures highlight that the minimum value recorded was 18 and the maximum was 75 with the first quartile equal to 22, third quartile equal to 28 and fourth quartile equal to 75. This distribution partially reflects heterogeneity of the population in Europe. The share of women in the EU is 51% (Eurostat,

2022), which is in line with the 53% of the survey conducted in this thesis. The share of women and men having completed tertiary education is around 40% (Eurostat, 2022). This is considerably lower than the current study. The reason is that data was collected through the network of the author and thus reflects an audience which has mostly attended university degrees. For the same reason, employment rate is lower compared to the EU average of 70% (Eurostat, 2022) as several respondents are still concluding their academic journey. Again, age distribution in the EU only partially mirrors the pattern in the survey. Eurostat data reveals that citizens are distributed equally between the ages of 15 and 29 years old (8.6%), 30 and 44 years old (10.1%) and 45 and 60 years old (10.7%) (Eurostat, 2020).

Further internal analysis of the survey is conducted through manipulation checks. The observed answers suggest that 93 participants matched the assigned AI Assistant to the customer service agent that handled their complaint, 8 provided a wrongful response. Moreover, 80 volunteers matched the assigned Human Employee to the customer service agent that helped with their support request. Similar proportions apply to the brand type. 93 participants correctly identified up-and-coming and technological brands (8 wrongful answers) compared to 85 who recognised the luxurious, well-known brands (15 wrongful answers). The Chi-square tests provide divergent results for agent and brand type. The former ($p - \text{value} = 0.031$) rejects the null hypothesis that the two categorical variables are independent. This means that there is a relationship between the categorical variables. The latter ($p - \text{value} = 0.089$) fails to reject the null hypothesis; therefore, the observed values are not different from the expected ones. Additionally, respondents deemed the scenarios as realistic. The ANOVA test indicates that the mean realism scores do not variate across scenarios ($p - \text{value} = 0.38$). Moreover, internal reliability is consistent as coefficients for the Cronbach's Alpha are > 0.7 ($\text{Customer satisfaction} = 0.86, \text{Repurchase intentions} = 0.82, \text{Service quality} = 0.97$). The Levene test shows that the variance across customer satisfaction, repurchase intentions and service quality are not significantly different from each other ($p - \text{value} = 0.31$). These findings suggest that the manipulations largely worked as intended.

The first hypothesis proposes that disclosure of AI agent in the response to a customer service enquiry on social media negatively influences customer satisfaction. The second hypothesis entails that such negative impact is mitigated (accentuated) if the brand is innovative (sophisticated). These hypotheses are tested through a two-way ANOVA. The results are provided in Table 6.

Two-way ANOVA: Customer Satisfaction

ANOVA

	<i>SS</i>	<i>df</i>	<i>MS</i>	<i>F</i>	<i>P-value</i>
Agent Type (0 AI, 1 Human)	30.851	1	30.851	14.589	< .001
Brand Type (0 Innovative, 1 Sophisticated)	0.653	1	0.653	0.309	0.579
Agent Type (0 AI, 1 Human) * Brand Type (0 Innovative, 1 Sophisticated)	3.153	1	3.153	1.491	0.224
Residuals	416.589	197	2.115		

Post Hoc Tests - Agent Type (0 AI, 1 Human)

Comparison							
<i>Agent Type (0 AI, 1 Human)</i>	<i>Agent Type (0 AI, 1 Human)</i>	<i>Mean Difference</i>	<i>SE</i>	<i>df</i>	<i>t</i>	<i>Ptukey</i>	
0	1	-0.799	0.209	197	-3.82	< .001	

Two-way ANOVA: Repurchase Intentions

ANOVA

	<i>SS</i>	<i>df</i>	<i>MS</i>	<i>F</i>	<i>P-value</i>
Agent Type (0 AI, 1 Human)	2.29E-04	1	2.29E-04	1.16E-04	0.991
Brand Type (0 Innovative, 1 Sophisticated)	0.735	1	0.735	0.372	0.543
Agent Type (0 AI, 1 Human) * Brand Type (0 Innovative, 1 Sophisticated)	6.98E-07	1	6.98E-07	3.53E-07	1
Residuals	389.568	197	1.978		

Two-way ANOVA: Service Quality

ANOVA

	<i>SS</i>	<i>df</i>	<i>MS</i>	<i>F</i>	<i>P-value</i>
Agent Type (0 AI, 1 Human)	115.80	1	115.80	64.62	< .001
Brand Type (0 Innovative, 1 Sophisticated)	4.48	1	4.48	2.5	0.12
Agent Type (0 AI, 1 Human) * Brand Type (0 Innovative, 1 Sophisticated)	19.90	1	19.90	11.11	0.00
Residuals	353.02	197	1.79		

Post Hoc Tests - Agent Type (0 AI, 1 Human)

Comparison							
<i>Agent Type (0 AI, 1 Human)</i>	<i>Agent Type (0 AI, 1 Human)</i>	<i>Mean Difference</i>	<i>SE</i>	<i>df</i>	<i>t</i>	<i>Ptukey</i>	
0	1	-1.55	0.193	197	-8.04	< .001	

Post Hoc Tests - Agent Type (0 AI, 1 Human) *
Brand Type (0 Innovative, 1 Sophisticated)

Comparison									
<i>Agent Type (0 AI, 1 Human)</i>	<i>Brand Type (0 Technological, 1 Sophisticated)</i>	<i>Agent Type (0 AI, 1 Human)</i>	<i>Brand Type (0 Technological, 1 Sophisticated)</i>	<i>Mean Difference</i>	<i>SE</i>	<i>df</i>	<i>t</i>	<i>Ptukey</i>	
0	0	0	0	0.947	0.252	197	3.76	0.001	
			1	-0.907	0.258	197	-3.52	0.003	
			1	-1.244	0.289	197	-4.30	< .001	
	1		1	-1.854	0.254	197	-7.29	< .001	
			1	-2.191	0.287	197	-7.65	< .001	
		1	1	-0.337	0.292	197	-1.16	0.654	

Table 6. Hypothesis Testing: Two-way ANOVA

Statistically significant differences arise for customer satisfaction and service quality. In detail, agent type for customer satisfaction, agent type and the interaction between agent type and brand type for service quality reject the null hypothesis that there is no difference in mean answers ($p - value \leq 0.001$). Table 6 also displays the related post hoc tests. Tukey p-value

shows that the disclosure of AI Assistant as customer service agent in social media yields lower customer satisfaction. In fact, the estimated marginal means demonstrate customer satisfaction mean is 4.89 when AI Agents are disclosed compared to 5.69 when Human Agents are disclosed. These findings support the first hypothesis. Similar conclusions are shown for service quality. Tukey p-value shows that the disclosure of AI Assistant as customer service agent in social media entails significantly lower service quality compared to Human Agents. The former customer support quality has a mean of 4.05, the latter of 5.60. In addition, the interaction between agent and brand demonstrate that the negative effect of AI agent disclosure is mitigated if the firm is innovative compared to sophisticated. In fact, the mean service quality jumps from 3.58 a 4.53. In contrast, service quality is always perceived as positive with human agent disclosure on social media. The mean response for technological brands was 5.43 and for luxurious brands was 5.77. These findings support the second hypothesis.

In conclusion, the thesis shows that respondents who are disclosed AI as their support agent in social media display lower satisfaction and service quality than respondents who are disclosed Human agents. Moreover, this impact is mitigated if the brand is innovative and accentuated if the brand is sophisticated. Nevertheless, the overall satisfaction and service quality for technological firms with AI customer service agents is not inherently negative, but rather neutral. In contrast, the perception of AI agents for luxurious brands in social media is mildly negative.

General Discussion

This section aims to highlight the contributions of the present thesis to academic and managerial knowledge. In detail, it provides a description of how the literature review, qualitative and quantitative study have contributed to reducing complexity on AI in social media customer care and have answered research questions proposed by other authors. Finally, it provides guidelines for managers and companies to implement AI as a service agent in a manner that maximises customer satisfaction.

Theoretical Analysis

The contribution of this thesis towards prior academic research is twofold: review and delimitation of current knowledge, analysis of artificial intelligence in social media customer care from the perspective of customers.

The existing academic literature has proposed conceptual or statistical analysis of AI as a tool in social media client care. The technical nature of these articles and documents resulted in the necessity to provide an overview of the technology. Therefore, this study has combined previous definitions of artificial intelligence and support on network platforms to define the technology and its use. In addition, it has delimited its definition and thus provided a theoretical background for future discussions: it has distinguished AI from statistical modelling and data mining and defined the output of the technology as natural language generation. Moreover, the literature review has collected uses of AI in social media customer care that do not directly involve responding to customer, including mood detection, automated routing, prioritisation and social listening. Though the literature review was not systematic, the present study provided a comprehensive analysis on current knowledge via the creation of a conceptual framework. In detail, it has identified two main categories of research: design and consumer behaviour. The former describe what model AI should follow and what algorithm should be selected. The latter refers to techniques for recognition of customer sentiment and definition of information useful to the customer. This exercise has highlighted the technocratic focus of academia and justified the necessity for higher attention to client perceptions.

The analysis of AI from the customers' perspective represents the most significant theoretical contribution of this thesis. Hu et al. (2018) affirm that research is necessary to understand end user engagement with AI agents. Ghouri et al. (2022) suggest that examination of AI in network platforms should occur from viewpoints other than executives and managers. Pitardi et al. (2021) highlight the need to examine the connection between customers and artificial

intelligence. In response, this thesis has interviewed fourteen consumers within the European Union to examine their perceptions of artificial intelligence within social media aid requests. A thematic analysis has resulted in a conceptual framework which defines the variables that impact client satisfaction when interacting with a corporation on social media and with a technological agent. Such variables are agent disclosure, query complexity, communication channel and brand image. Furthermore, a moderation effect was noted for sentiment and past experience.

Moreover, prior research was extended through the investigation of two design elements: AI agent disclosure and the role of brand image. Hazée (2021) requests analysis about the impact of AI agent disclosure on support within social media. Vlacic et al. (2021) question the acceptability of AI and the relative trust as well as emotions that consumers experience when interacting with the technology. The empirical quantitative analysis evaluated the hypothesis that disclosure of AI vs. human agents in the response to a customer service enquiry on social media negatively influences customer satisfaction. In addition, several papers reported the necessity to extend knowledge on the role of brand image. In fact, Xu et al. (2017) propose a study on the impact of chatbots on customer perceptions of brands and Hu et al. (2018) suggest the application of their model to brand and style-aware algorithms. As proposed above, the empirical quantitative analysis verified the hypothesis that the negative impact of the disclosure of an AI agent on satisfaction is mitigated vs. accentuated if the brand is innovative vs. sophisticated. Respondents to the survey were required to understand the impact of a brand type, described as either up-and-coming and technological or luxurious and well-known, on the customer service provided, *ceteris paribus*.

Managerial Recommendations

This section of the thesis provides insights on how managers and corporations can implement AI in their customer service offerings. This is relevant as positive interactions with customers allows higher economic performance (O'Brien, 2021).

Consumers are increasingly adopting social media for customer service purposes and they are expecting immediate or fast replies (Benmark et al., 2012). The adoption of AI represents a business opportunity as it allows to answer any query immediately without waiting for an available employee. This benefit was highlighted in multiple interviews. However, the quantitative analysis suggested that AI is perceived more negatively than personnel. This effect is exacerbated for luxurious or sophisticated brands. According to the conceptual framework in the qualitative analysis, a potential reason could be previous experiences. Historically, AI

assistants in phone calls or chatbots in websites are not able to provide support for queries which are not frequently asked or which require complex solutions. In addition, consumers find the interaction with AI time consuming as they often are required to answer several questions before reaching a solution. In contrast, directly communicating with a human agent would allow to immediately present an issue and identify an explanation. Yet, academic literature has developed technical solutions to make AI agents efficient, effective and empathic. Therefore, companies that wish to adopt social media care and benefit from its lower costs (Benmark et al., 2012) must enact two strategies. First, the brands should build an AI service which is as close to human beings as possible in terms of solution proposal and empathy. Second, they must market to their client base the innovation. It is necessary to both inform and convince customers that AI in social media would be as or more beneficial than traditional communication channels. If either of these two solutions are not satisfactory, the company might risk losing the client or creating negative word-of-mouth. Hence, it is advisable to deliver AI agents in social media via traditional workflow processes. In this manner, brands are able to build the algorithm and extensively check its functioning. In contrast, an agile implementation of AI would require consumers to experience difficulties as the technology develops. This might result in discouragement and confirmation of negative biases.

It is also worth noticing that service quality for AI disclosure is not inherently negative in technological and innovative brands. Managers in such corporations are allowed to experiment and propose artificial intelligence to their clients with more ease. This could be specifically true for companies that are oriented towards innovator and early adopter clients. This is in counter position to luxurious, sophisticated brands. In this scenario, the use of AI is perceived as negative. A potential explanation could be that established companies usually offer their products or services at a higher price. Thus, customers might feel entitled to more attention and personalised support. The analysis provides no impact of AI on repurchase intentions. The reason could be that the post published by the company provides a concrete and immediate resolution. Manager could adopt this strategy to improve customer satisfaction.

Consumers interviewed have shown that the main objective of customer service is to fix problems fast. Often, they are not interested in quick replies that do not provide a solution or long waits that figure out problems. Therefore, if the company does not wish to purchase or develop an AI software which is accurate with simple and complex queries, it might be valuable to use artificial intelligence as a support tool for human agents. The technology could function to identify posts with the highest priority, provide preliminary solutions to an employee which then evaluates them and define the mood of the client.

From an organisational standpoint, Fountaine et al. (2019) suggest that the adoption of artificial intelligence should follow four actions. First, leaders should develop compelling arguments and storylines to create motivation within the organisation and reassure that AI will not diminish or eliminate jobs. Second, managers should anticipate unique barriers to change by reviewing past initiatives, aligning AI projects to the brand's values and hiring expert profiles. Third, companies should budget as much for integration and adoption by current practices as for the development of the technology (Fountaine et al., 2019). Fourth, managers are required to organise for scale and balance time investments with value delivered.

Conclusion

This final section proposes a brief summary of the entire study. The next paragraphs will follow the structure of the thesis and highlight the most relevant contributions. Then, the study points out limitations and further research questions that arise from the analysis.

The paper started by proposing the research motivation. It specified that companies are increasingly adopting social media as a tool to deliver customer service. The reason is to leverage network platforms' potential to gather client feedback, treat client requests and issues, exchange consumption experiences. Though organisations have employed human agents or technology-based means, they frequently are unable to meet consumers' expectations. A potential solution is represented by artificial intelligence, which is capable of interpreting data and learning from information to provide client support. Companies perceive algorithms can deliver more efficient business processes, yet there is uncertainty on their ability to provide satisfactory responses in customer service interactions. In addition, academic research on the field is scarce and mostly focused on data or statistical analysis. Therefore, it appears there is limited attention to consumers' insights and perceptions. In this context, the thesis proposes to analyse the impact of AI on social media customer care via the perspective of customers. It proposes to define the boundaries of artificial intelligence in providing support within network platforms, define which interaction characteristics favour the use of the technology and verify such hypotheses via empirical research.

To expand knowledge on AI in social media client support, the thesis proposed an analysis of the two factors composing the research question: social media customer service and AI. The former is defined as advice or assistance offered to a client and is comparable to customer care for the purposes of this study. A key parameter for the evaluation of support is customer satisfaction. In the realm of social media, this requires companies to offer a reliable, responsive and empathic service. The definition of AI is twofold. Academia proposes the technology as either a tool to examine consistent amount of information in a rigorous and precise manner or a tool to mimic human behaviour and interactions. The applications of the technology have been defined across academic literature. Authors have identified artificial intelligence as a solution to optimise marketing processes, from gathering and interpreting unstructured data to improving business and strategic decisions, and contribute to customer service via machine learning and language capabilities.

Within the domain of AI in social media customer care, the thesis contributes by proposing a definition and delimiting the boundaries of the technology. In detail, artificial intelligence for

network platform support is described as a rational agent capable of understanding social media support requests initiated by individual customers and proposing favoured solutions through imitation of human behaviour and communication. In the context of this definition, AI is concerned with the field of machine learning, i.e. identifying patterns of information and predicting future requests or solving client issues. In contrast, AI is not identified with statistical modelling and data mining. It functions through unstructured data, which is analysed via two main processes: problem solving and reasoning. Moreover, the output of AI is natural language processing: manufacturing of complete conversations. The most relevant example of such technology is represented by chatbots.

Academic literature and related reviews on AI in social media customer care is scarce. This thesis provided an overview of the topic by integrating previous publications into two categories: design and consumer behaviour. The former refers to the building processes and structures of artificial intelligence. This is the predominant field of study, accounting for four papers. The latter is related to the analysis of consumers' actions and reactions during conversations with AI on social media. This topic was analysed by three papers. In further detail, design elements were two: conceptual and technical. Conceptual elements concern the development of an AI model that ensures effective response to customers' posts. Technical elements provide indications on the collection of unstructured data and the identification of machine learning algorithms for its interpretation. Consumer behaviour is also structured into two categories. Emotional elements refer to the identification of sentiment; rational elements are relative to the provision of information to solve issues.

The literature review above concluded that current knowledge on AI in social media support is highly focused on technocratic analysis. Nearly the totality of research proposes statistical solutions to improve the effectiveness of the technology. It is evident that building empathic and precise algorithms is solely a first step in reaching customer satisfaction when requesting aid. As understanding of clients on this topic is limited, the thesis has developed an exploratory qualitative analysis via interviewees to fourteen volunteers in the European Union.

The themes that emerged from this exercise are four: agent's nature disclosure, complexity of query, communication channel and brand image. The agent's nature was divided between human and artificial intelligence. Human agents were perceived as inherently positive, AI agents were inherently negative or neutral (for a minority of participants). Some interviewees attributed the adverse attitude towards AI to a lack of attention from companies in supporting their clients. A limited number of volunteers had a neutral stance towards technological agents as their primary objective was to solve their query efficiently and timely, independent of agent

type. Complexity of query was categorised in two forms: complexity of the request and complexity of the interaction. Artificial intelligence was deemed suitable for low complexity or recurrent problems. These two themes were moderated by two other variables, namely sentiment and past experiences. A third theme was the communication channel: AI on social media was perceived as a last resource or emergency solution. Finally, brand image appeared to have significant influence on consumers' satisfaction. Innovative, tech-oriented brands were believed suitable for AI agents on social media, whilst established or luxury brands were not appropriate for technology support.

Through the combination of literature review and exploratory qualitative findings, the thesis suggested two hypotheses: disclosure of AI vs. human agent in the response to a customer service enquiry on social media negatively influences customer satisfaction and the negative impact of the disclosure of an AI agent on satisfaction is mitigated (or accentuated) if the brand is innovative (or sophisticated).

These hypotheses were tested via experimentation. 278 responses were collected through an online survey. The sample of population that participated was not representative of the European Union population. Though the ration between male and female volunteers was similar to Eurostat data, the number of individuals that completed tertiary education and were unemployed was significantly larger than the EU average. In addition, the median age was highly left skewed. Nevertheless, the validity of the dataset was largely confirmed through analysis of survey data. Respondents deemed scenarios realistic and internal reliability was consistent. Moreover, the Levene test showed that variance between customer satisfaction, repurchase intentions and service quality was not statistically different. However, the Chi-square test for agent type showed that manipulations were not fully successful. The p-value was lower than 0.05, thus suggesting a potential relationship in categorical variables.

The analysis of data showed that agent type for customer satisfaction, agent type and interaction between agent type and brand type for service quality reject the null hypothesis that there is no difference in mean answers. In detail, the disclosure of AI Assistant as customer service agent yields lower customer satisfaction and service quality compared to Human Agents. Furthermore, the negative effect of AI agent disclosure is mitigated if the brand is innovative compared to sophisticated. It is worth noticing that overall satisfaction and service quality for technological firms adopting artificial intelligence support in network platforms is not inherently negative, but rather neutral.

The thesis concluded by suggesting AI is a business opportunity as it allows to answer any request on social media quickly. To counterbalance the negative impact of consumers' past

experience with the technology, managers are required to enact two strategies. First, they have to develop an algorithm that is as close to human agents as possible in terms of suggesting solutions and being empathic; second, they must market AI to their client base. To ensure customer satisfaction, managers are also advised to develop the customer service tool via traditional waterfall models. Finally, managers must acknowledge that technological and innovative brands can experiment with AI in network platforms, especially if their clients are mostly innovators and early adopters. In contrast, if a company is not willing to purchase or develop an algorithm for support, it can utilise AI as a tool for human agents.

Limitations and Further Research Questions

This thesis investigated the impact of AI on social media customer care from the perspective of consumers. It identified that the disclosure of an artificial intelligence response has a negative effect on customer satisfaction and on service quality. This effect is moderated if the brand is perceived as innovative and exacerbated if it perceived as sophisticated. Such findings and the paper's limitations allow opportunities for future research.

To start with, the literature review was not conducted through a systematic analysis. Though research for papers in the field spanned multiple online libraries and databases, some articles might have been excluded from the analysis. Future studies should verify and examine if other papers are available.

In the second place, the exploratory qualitative analysis relied on fourteen interviews whose participants had lived and grew up in developed Western countries. The study could be replicated in considering a more varied sample of individuals and cultures. Take, for example, the role of context. In low-context cultures, communication is expected to be clear, to-the-point, simple. Information is analysed at face value and repetition is appreciated as it enables clarification (Meyer, 2014). In high-context cultures, communication is sophisticated and layered (Meyer, 2014). Information is frequently implied and requires to be interpreted. The result is that opinions on AI might be diverge for different cultures. For instance, high-context cultures might have a strongly negative perception of AI in social media customer care as it only communicates precise data. Another future research could be conducted by interviewing individuals that already have had previous experiences with AI in social media client support. The present thesis concentrated on consumers that both encountered the technology in network platforms and that possessed network platforms accounts but did not use the technology. This could potentially bias the thematic analysis and the consequent hypothesis development.

Academic literature could select volunteers who previously declare their knowledge of the field.

In the third place, a number of limitations and future research questions can be derived from the empirical quantitative study. Volunteers were heavily left skewed in terms of age and the majority completed tertiary or higher education. Moreover, the share of employment was lower than the population average as students replied to the survey. Future studies should consider performing the same experiment on a sample that is representative of the European or local population. In addition, one manipulation check for the survey displayed that there was a significant number of errors in the identification of the assigned scenario for the agent type. The consequence of these mistakes is twofold. Respondents could have answered the questions based on the assigned scenario but registered the wrong answer in the manipulation check or could have answered in the manipulation check the response on which their evaluations of the entire survey were based. A posteriori evaluation of this issue is not feasible through online survey. This could be overcome with a larger sample, which would reduce the incidence of errors in the analysis, or by modifying the experimentation, for example one could utilise observation techniques. A further limit of the quantitative analysis is the absence of scenarios testing only one categorical variable. Future literature could test the effect of the agent type on customer satisfaction with no brand image moderation and vice versa. Furthermore, the complexity of issue should be tested by introducing two new scenarios: high complexity solution vs. low complexity solution. One further manipulation to the test conducted in this thesis could be to modify the response post from the company so that it does not offer publicly a recovery option. The benefit would be to verify the impact of AI in repurchase intentions. This could be structured based on the work from Hogreve et al. (2019). For example, the conversation on social media could be the following.

You write this post: “@_brandname_ your product is faulty. It just broke down! This is very inconvenient”.

The brand replies to your post: “Hi Customer, please send us a private message with your details, including the order number, address and description of the item, so that I can examine the problem – Kobe, AI customer service agent” or “[...] – Alexander, customer service employee”

Finally, future endeavours could test the difference in perception from customers between AI in social media customer care and AI in traditional communication channels. The mediating

effect of sentiment and previous experience should also be considered as a potential research question. For example, surveys could declare to respondents that AI is capable of solving any issue in a reasonable number of questions. From a managerial perspective, businesses could benefit from two further studies. First, it is necessary to contact local companies of various dimensions to understand the NPV and implementation process of an AI software which reflects the technical models provided by literature and would ensure positive customer satisfaction as well as service quality. Second, analysis should be conducted on the impact of AI as a support tool in customer service on social media. It is useful to understand the impact of the tool and the perception of customers compared to response creation algorithms.

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Executive Summary

This thesis analyses the impact of AI on social media customer care from the perspective of consumers. The reason is twofold. First, a comprehensive literature review on the topic showed that current published articles focus on technical characteristics of the technology. Second, business can derive added value from understanding the interaction and relationship their customers establish at every contact point, including aid requests on network platforms. The thesis conducts a thematic analysis via interviews to explore which variables affect customer perceptions of AI. Findings suggest that the most relevant themes for consumers are agent disclosure, query complexity, communication channel and brand image. Two of these themes, i.e. agent disclosure (AI vs human agent) and brand image (innovative vs sophisticated), are tested. The study finds that communications from artificial intelligence in social media negatively impacts customer satisfaction as well as service quality. In addition, the interaction between agent type and brand image also affects service quality. Finally, this thesis concludes by suggesting further research questions, including the test of message complexity and the manipulation of publicly offered recovery solutions.