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Chatbots for Customer Service: the Case Study of ANAS

1. Introduction

In today's digital society many businesses have decided to expand the range of tools they can use to maintain more stable and long-lasting relationships with their customers. In this scenario, chatbots represent a new frontier and can be defined as conversational agents that can engage in a two-way relationship with users, providing them with answers and information on a round-the-clock basis, without queues and with a text-based interface (Hatwar *et al*., 2016; Khanna *et al*., 2015). Chatbots offer businesses the twofold advantage of being both time and cost-saving by automating certain processes while human employees can be assigned to more complex tasks (Dorotic *et al*., 2023; Ischen *et al*., 2019; Ukpabi & Karjaluoto, 2017). They can also increase customer loyalty by offering alternative ways of communicating with a business and providing users with more digitised, transparent, effective and innovative services (Belk, 2013; Fryer *et al*., 2017; Hill *et al*., 2015; Kumar *et al*., 2016; Shumanov & Johnson, 2021).

Large international IT companies, such as Google, Facebook, IBM and OpenAI, were the first to experiment with the use of chatbots. This has helped them perfect their systems, which can now process large amounts of data to address a broad range of queries and requests. The system is driven by artificial intelligence (AI), automated rules, natural language processing (NLP) and machine learning (ML).

The literature has also analysed the determinants of customer satisfaction when using chatbots (Ashfaq *et al*., 2020), with the following key findings:

- There is a positive impact on user satisfaction if a chatbot provides up-to-date and reliable information, quick responses and tailored attention.
- Customers are more satisfied and willing to continue using a chatbot if it's easy to use, useful and fun.
- Although digital technologies can offer efficiency and effectiveness, they can sometimes frustrate users by failing to meet their needs/desires.
- Even though users tend to find the service provided by current chatbots pleasant and satisfying, they may occasionally prefer to interact with human beings, as long as it increases user productivity.
- Finally, the service provider should ensure that the e-chatbot service is hassle-free, helpful, useful, and enjoyable.

The use of chatbots is becoming increasingly widespread also outside the United States (Jiang *et al*., 2022; McTear *et al*., 2016; Waxer, 2016). In Italy, for example, the use of chatbots by businesses is growing, although to a lesser extent than in other countries. According to research conducted by Osservatori Digital Innovation in 2024, 23% of large Italian businesses are already using chatbots, up by 10% compared to 2023[6]. The main areas of use of chatbots in Italy are customer service (customer queries, technical requests, information), marketing (promotion of products and services), human resources (management of employee requests, HR processes), and sales (appointment scheduling, commercial negotiations).

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[6] https://www.osservatori.net/it/prodotti/formato/insight/conversational-ai-chatbotvirtual-assistant-esperienza (Date of Access: 9 August, 2024).

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One of the Italian companies engaged in changing the way it communicates with its users (alongside TIM, Enel, UniCredit), in line with contemporary innovation processes, is ANAS Spa, which is in the business of managing and maintaining roads and road infrastructure, managing a network of approximately 32,000 kilometers of state highways and motorways of national interest, with around 6,800 employees, including road workers, engineers and architects.

In January 2018, ANAS joined the "Ferrovie dello Stato Italiane Group", as part of its "Transport Infrastructure Hub", established by the Group alongside "RFI" (Lead Partner), "Italferr", and "Ferrovie del Sud Est". The aim of this integration is to strengthen collaboration among the Hub member companies, to develop integrated road and railway infrastructure projects. These efforts are designed to accelerate investment and are subject to oversight by the Ministry of Infrastructure and the Ministry of Economy and Finance, which covers both the governance of the company and its operations, in particular with regard to economic and financial planning activities and agreements with the concessionaires (Giovannini, 2010).

The activities of ANAS encompass the operation of roads and motorways, including regular and extraordinary maintenance, and the upgrading and improvement of the Italian road network and relevant signage. The company is also engaged in the construction of new roads and motorways, both directly and under concession agreements with third parties, as well as providing user information services and implementing road and motorway safety measures. Last but not least, the company engages in research and development activities related to roads, traffic and transportation.

Given the role ANAS plays in managing Italy's road infrastructure, maintaining effective communication channels with the general public is of crucial importance and setting up an effective Customer Service capable of responding to the queries and needs of the public, addressing their requests and reports, is essential for fostering direct engagement with ANAS. The company has therefore made several contact channels available to users, such as the "Pronto Anas" Customer Service, tasked with providing accurate information about the company, its activities, and services to customers, as well as responding to requests and assess reports or complaints. In order to improve this service, ANAS has strategically introduced and integrated modern digital contact and traditional communication channels, such as contact centres and emails, to broaden access and improve response times. At the end of 2022, the company inaugurated two new digital communication channels, via Telegram and WhatsApp, to enable users to interact with ANAS at any time, streamlining communication management and offering "asynchronous" channels for quick direct interaction. These platforms were chosen because of their widespread use and user-friendliness, allowing users to communicate seamlessly with ANAS without having to navigate their way through complex interfaces. At the heart of the service is an AI bot-based customer support system designed to provide quick and efficient assistance. The chatbot was developed to offer multiple levels of interaction and support, providing an effective solution capable of streamlining communication and enhancing the user experience. When users interface with the service, through either Telegram or WhatsApp, they are greeted by a bot designed to understand and respond to a wide range of common queries and requests, providing useful information, detailed instructions or solving the most critical issues. Thus, most queries can be dealt with swiftly and effectively, reducing the need for traditional phone queues and improving accessibility. Furthermore, the virtual assistant is always available. More specifically, the chatbot is able to provide answers according to three levels of interaction: self-explanatory answers (for example to questions such as "How do I send a job request to ANAS?"); answers with a suggestion to open a ticket for issues that require further investigation by the ANAS district offices (for example, when reporting bad road surface conditions), with the convenience for customers of being able to attach all the necessary information, including the exact coordinates of the reported spot in real time, and subsequently receive the relevant feedback; and, thirdly, answers with a suggestion to contact one of the contact centre operators directly via WhatsApp or Telegram.

The chatbot is integrated with the request management platform operated by the Customer Service department. This two-tier system effectively balances automated efficiency with human intervention,

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when necessary, consistently with ANAS's commitment to innovation and digital transformation. This approach can achieve two different objectives, increased customer satisfaction and optimising day-to-day contact centre activities. This hybrid system is in line with the company's innovative vision, which aims to build a digital ecosystem in which customers can easily move from one channel to another. Furthermore, the Customer Service can guarantee high-level performance by adopting a process measurement and monitoring system based on the use of indicators, which the company uses to measure and oversee service performance improvement.

The purpose of this study is to report on the interactions between ANAS users and the company's chatbot, highlighting the requests, preferences and needs of the former and the automated response and support capabilities provided to them, while also investigating the point of view of the chatbot users. The study also focuses on the chatbot's ability to provide an accurate and satisfactory response that does not require further intervention from human operators, who are instead called on to provide second-level assistance, when necessary.

2. Use of AI-based chatbots in the public sector

The history of chatbots dates back to the 1950s, when the Turing Test prepared the groundwork for developing intelligent conversational agents (Wawrosz & Jurásek, 2022). Over time, chatbots have evolved into two main types, (1) linguistic (or rule-based) chatbots, which are based on predefined rules or decision trees, and (2) AI chatbots, which utilize NLP and ML to learn from interactions and improve over time. AI-based chatbots can be further broken down according to their level of AI usage, ranging from minimal AI involvement, such as in simple query responses or order processing, to advanced applications with more complex interactions and decision-making capabilities (Caldarini *et al*., 2022). For example, chatbots with minimal AI use, such as Apple's Siri or basic FAQ bots, are programmed to perform specific tasks strictly according to *ad hoc* parameters. Conversely, advanced chatbots use AI to simulate human-like decision-making processes, enhancing their ability to provide tailored services and interact seamlessly with other systems (Perez-Marin & Pascual-Nieto, 2011).

The use of AI technologies in the public sector, particularly AI-based chatbots, represents a transformative force that is reshaping the way businesses and organizations interact with citizens and deliver public services. This integration of AI into the public sector is part of a broader trend towards digitisation and data-driven decision-making. This shift began in the 1990s with the digitisation of government records and the automation of routine tasks, laying the groundwork for more advanced AI applications (Villagrasa, 2020). In the early 2000s, the rise of e-government initiatives further accelerated this trend, with chatbots and decision support systems playing a crucial role in improving public service delivery and citizen engagement (Criado & Gil-Garcia, 2019). Today, AI-driven public services encompass a wide range of applications, from predictive policing and smart city initiatives to customised healthcare and automated welfare systems.

The use of AI-based chatbots in public services offers several significant benefits. Chatbots can provide continuous support, allowing members of the public to access information and services at any time and from anywhere. This constant availability reduces the need for large-scale human resources, resulting in cost savings. In the business environment, automating customer service with chatbots has reduced call and email volumes by up to 70% (Wang *et al*., 2022). Similar efficiencies can be achieved in the public sector, where resources are often limited. For example, the US Citizenship and Immigration Services uses a chatbot called Emma to manage common inquiries, streamlining the process and freeing up human staff members for more complex tasks (Villagrasa, 2020). Chatbots can handle legal inquiries and assist emergency services by providing real-time information and assistance. By using NLP and ML, chatbots can engage in more natural and interactive conversations with members of the public, making it easier for them to access the services and information provided. This customisation fosters a

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more user-friendly experience and can increase public trust in the institution they are interfacing with (Aoki, 2020).

AI chatbots can also analyse large amounts of data generated from interactions with the public, to identify patterns and trends. This information can be invaluable for policymaking and resource allocation, helping stakeholders to make more informed decisions (Bannister & Connolly, 2020). Furthermore, chatbots equipped with advanced AI capabilities can analyse data to detect potential fraud or identify risks, such as predicting fires or identifying false reports (Paluch & Wirtz, 2020). This proactive approach enhances public safety and minimises the likelihood of adverse events.

Despite the considerable benefits associated with the use of AI-based chatbots in the public sector, there are a number of challenges and ethical considerations that need to be addressed. One of the primary concerns is the potential for AI to undermine democratic processes and transparency. The opacity of AI algorithms and their decision-making processes can give rise to issues of accountability and fairness, especially if the technology is perceived as overly technocratic or biased (Neumann *et al*., 2024). This concern is particularly relevant when chatbots are used in sensitive fields, such as law enforcement or social welfare, where the fair and ethical treatment of persons is paramount. Furthermore, the implementation of AI technologies in the public sector requires careful consideration of privacy and data security. Given that chatbots often handle sensitive personal information, robust measures must be in place to protect personal data and ensure compliance with legal and regulatory standards (Furman & Seamans, 2019). Public trust in AI systems heavily depends on these safeguards being transparent and effective.

3. Research method

To achieve the research objectives, a comprensive qualitative-quantitative analysis of the textual material collected between December 2022 and July 2023 was undertaken, to assess the effectiveness of the chatbot in handling user interactions and to identify space for improvement in the customer service. The dataset for the analysis consists of 4,252 conversations (433 from Telegram and 3,819 from WhatsApp).

Phase one of the analysis consists of a quantitative study conducted to measure the frequency of interactions, temporal trends, and the main reasons for user engagement with the chatbot. This phase aimed to provide an overarching view of how users interact with the new digital channels (Telegram and WhatsApp) provided by ANAS. Key metrics, such as the number of successful interactions where user requests were resolved by the bot and the number of cases where human intervention was required, were calculated to evaluate the overall efficiency of the bot.

Following this quantitative assessment, a more in depth qualitative analysis was conducted, based on a hermeneutic approach, to understand the nuances of user interactions. This involved a thorough examination of the conversations to identify specific patterns and recurring critical issues (Barbeta-Viñas, 2024).

Subsequently, key themes were recognised to identify the main areas of conversation. The pre-processing of the textual data involved several steps for preparing the conversations for analysis. The first step, data cleaning, involved removing unnecessary elements, such as emoticons, special characters, numbers, and other non-textual information that could potentially distort the analysis. In addition, common stop words that did not contribute to the understanding of the content, such as articles, prepositions, and conjunctions, were filtered out to minimise noise in the data. Once the data had been cleaned, the text was broken down into individual words and normalised to standardise the text data. This involved converting all characters to lower case and applying either stemming or lemmatisation techniques. Stemming reduces words to their root form, while lemmatisation reduces words to their base or dictionary form. These operations were useful to group together similar words and reduce the dimensionality of the dataset, thereby increasing the effectiveness of the analysis.

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In parallel, a sentiment analysis was carried out using advanced natural language processing (NLP) techniques. Sentiment analysis aimed to measure the emotional tone of user messages and categorise them into positive, neutral, or negative sentiments (Wankhade, 2022).

The use of NLP for sentiment analysis is fundamental because it enables the interpretation and analysis of opinions, feelings and emotions expressed in written language (Kavitha *et al*., 2023). NLP is a branch of artificial intelligence that deals with the understanding and processing of human textual and vocal language. NLP is important in sentiment analysis for the following reasons:

- Contextual knowledge: by understanding the context in which words are used, distinguishing between literal and figurative meanings.
- Processing unstructured data: by analysing large amounts of unstructured data, such as social media posts, product reviews, and conversations, to extract useful information.
- Automation: by automating the sentiment collection and analysis process, saving time and resources.
- Decision Support: by providing companies with valuable insights into consumer sentiment, helping them to create targeted brand messages and better understand customer preferences.

In short, NLP is essential for sentiment analysis because it can help in processing and interpreting human language at scale, providing insights and supporting data-driven business decisions (Bing, 2020).

In this study, sentiment analysis used a Long Short-Term Memory (LSTM) neural network model, a technique known for its ability to capture context and sentiment in sequential data. LSTM is particularly effective for sentiment analysis because it can remember the order of words and their relationships over time, providing more accurate and nuanced interpretations of user sentiment.

To ensure the accuracy of sentiment analysis, the pre-processing phase was carefully designed to include all relevant linguistic features. This included checking the dictionary used in the analysis to ensure that it covered adversative conjunctions (e.g., “but,” “however”), negation adverbs (e.g., “not,” “never”), and other forms that may appear neutral but can imply negative sentiments. Such linguistic elements are crucial, as they can significantly alter the meaning of a phrase or sentence, thus affecting the overall sentiment score. An extensive review of the sentiment dictionary by reaserchers ensured that these elements were appropriately categorised and weighted to reflect their true sentiment value.

4. Results

During the reporting period, the chatbot handled a monthly average of 532 contacts. The most frequently used channel was Whatsapp, with an average of 477 monthly contacts, while Telegram featured a monthly average of 54 contacts.This gap can certainly be attributed to the fact that the former instant messaging platform is much more popular than the latter. Regardless of the contact channel, however, the researchers observed a fluctuating trend in interactions, with a drop in contacts between February and April, followed by a gradual recovery in the following months (*Fig. 1*).

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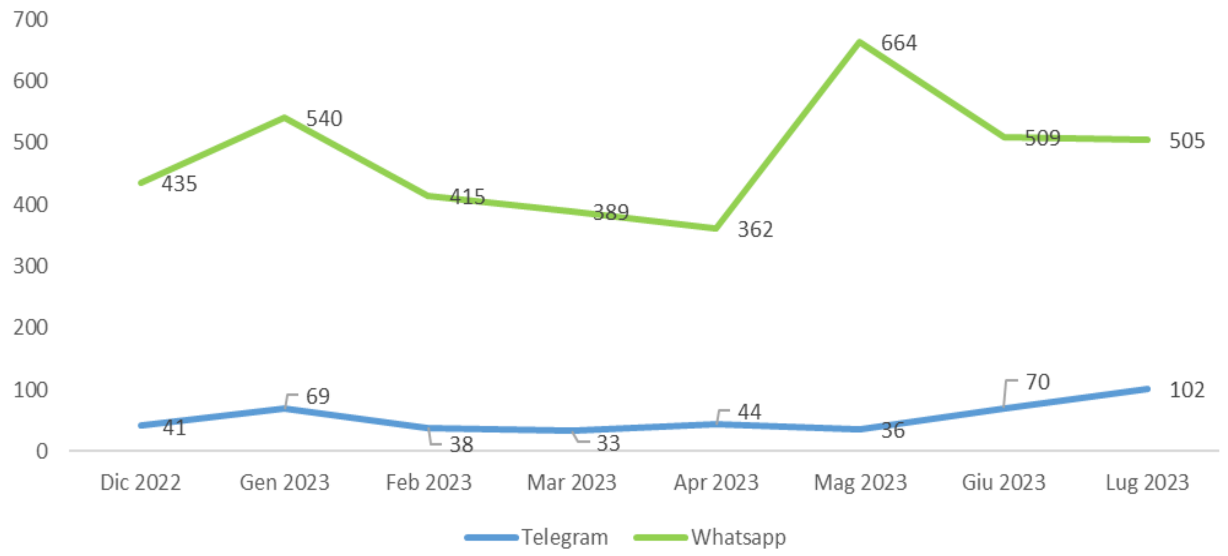

Fig. 1 – Trend in interactions on a monthly basis

By shifting the focus of the analysis to the contact hours (*Fig. 2*), it can be argued that the flow of interactions is continuous over the 24 hours. In fact, there are no empty time slots.

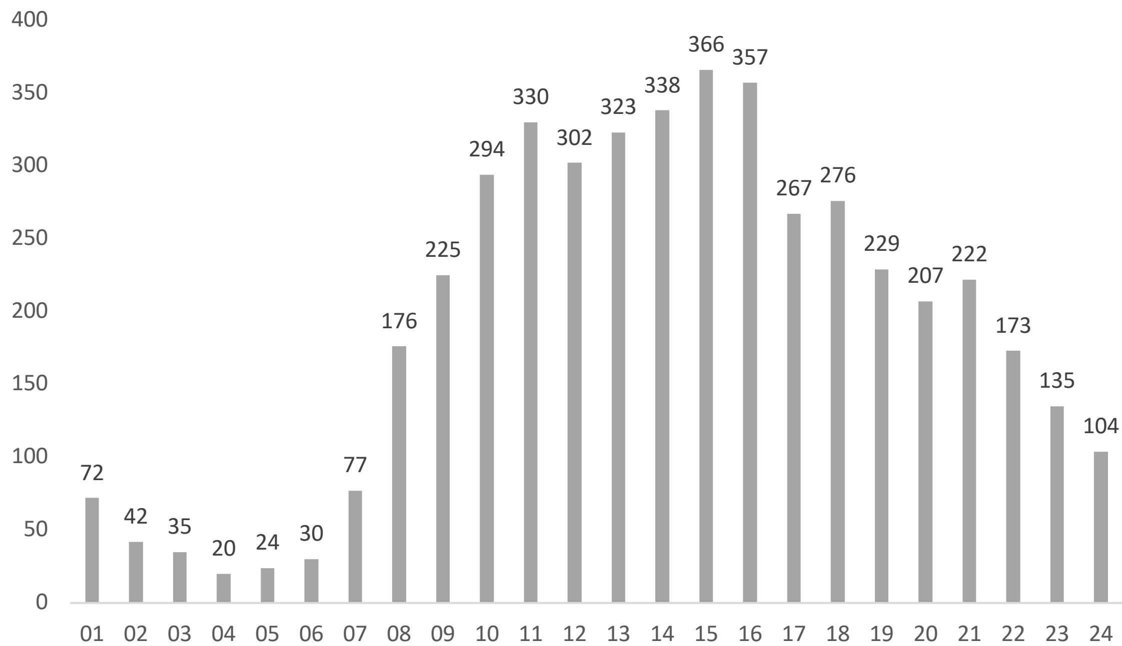

Fig. 2 – Trend of interactions on an hourly basis

The contact analysis suggests that interactions intensify starting at 7 a.m. and gradually increase throughout the day, peaking between 2 p.m. and 4 p.m. There are no significant differences between WhatsApp and Telegram (in percentage terms).

The possibility of interacting with the chatbot on a round-the-clock basis shows the willingness of users to communicate with ANAS even in those time slots not covered by the traditional customer service, which is active from Monday to Friday, from 8 a.m. to 8 p.m., excluding holidays, to collect suggestions and complaints or provide information.

The analysis also aimed to identify the profile of the users who used the chatbot. In fact, during the interaction, in fact, people who contact the customer service via Telegram and

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WhatsApp are asked to qualify themselves by identifying as either "customers", "businesses", "institutional players", "professionals" or "media representatives".

	Telegram	WhatsApp	Total
Businesses		0.51%	0.45%
Customers	99.37%	98.63%	98.70%
Institutional players		0.07%	0.06%
Media representatives		0.05%	0.04%
Professionals	0.63%	0.75%	0.74%
Total	100%	100%	100%

Tab. 1 – User profiles

Table 1 shows that "Customers" account for the majority of users for both channels. Moreover, both channels also feature "Professionals", despite representing a small percentage of the overall audience. WhatsApp emerges as a more diverse channel compared to Telegram, with a greater variety of user categories. In fact, although less frequently, "Businesses", "Media representatives" and "Institutional players" also find it useful for their automated interactions with ANAS.

	Telegram	WhatsApp	Total
1. Traffic information	18.78%	12.48%	13.13%
2. Road safety and emergencies	0.84%	4.34%	3.98%
3. Information	67.30%	61.23%	61.85%
4. Reporting	6.12%	9.40%	9.06%
5. Complaints	2.53%	4.65%	4.43%
6. Thank you messages	1.27%	0.48%	0.56%
7. Appointments	0%	0.27%	0.24%
8. Motorway news	3.16%	7.16%	6.75%
	100%	100%	100%

Tab. 2 – User profiles

Before starting the conversation with the chatbot, users are asked to specify the reason for their contact. *Table 2* provides an overview of the reasons prompting members of the public to use the ANAS chatbot. The request for "Information" (3) is the main reason for using both channels. Traffic inquiries (1) are more common on Telegram than on Whatsapp. In percentage (as well as absolute) terms, users favour WhatsApp to send complaints or reports. In both cases, the percentage of requests for appointments and thank-you messages is low.

In the next step, a hermeneutic approach was used to analyse consumer narratives, to identify critical aspects of their experience. This hermeneutic analysis, based on the philosophy of hermeneutics, focuses on interpreting texts to gain a deeper insight into how individuals build and communicate their experiences (Ricoeur, 1981). The process began with the adoption of the hermeneutic circle, which posits that understanding is achieved through an iterative process of moving between the text as a whole and its constituent parts (Thompson, 1997). The first thing researchers do is to read the entire material to grasp its general meaning, subsequently moving

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on to examine specific parts that seem to carry meaning. This process was repeated several times, allowing new insights to emerge as understanding deepened with each iteration.
The analysis then moved into a more interpretive phase, adhering to the iterative nature of the hermeneutic cycle. This involved a strategy of dialogical engagement, both with the text and among researchers (Gadamer, 1975).

The analysis shows that users did not always use the chatbot's decision tree correctly. This may be partly due to the fact that some of the entries are ambiguous. For example, choices 1 and 3 both contain the word "information." Likewise, similar conversations were conducted as both "reports" (option 4) and "emergencies" (option 2).

Another critical issue that has emerged from the analysis of the conversations is relative to the rate of interrupted communications (i.e. cut short before completion). The data analysis showed that about half of the people (45.9%) closed the chatbot before reaching the end of the conversation. This data is mainly related to two reasons, one originating externally and one internally. With regard to the former, the success of conversations via Telegram and WhatsApp is closely linked to the quality of the devices (smartphone, PC and/or tablet) and connection used by customers. As a result, technical problems may have affected the completion of the conversation. With regard to the internal causes, related to the functioning of the chatbot, the hermeneutic analysis highlighted how many users give up on continuing the conversation to the end, wearied by the long-winded request for socio-demographic data and by the consent formalities for authorising the use of the data, which, however, is required by the current legislation. A critical aspect is that even users who had already interacted with the bot in the past, providing their data and the necessary consent, are required repeat everything all over again. This renewed request can discourage people from repeatedly using the new communication channels, perceived as slower to process requests rather than providing faster and more immediate communication. During the conversation, users are asked to specify the route (or road) of interest to the user, but the validity of this request can only be verified later on because the system is unable to automatically immediately indicate whether or not the specific request can be processed. This impasse can be overcome – in the case of conventional calls involving a human operator – because then can verify in real time during the conversation whether the route of interest is among those managed by the company.

Among the successful converstations, a high percentage of problems were solved exclusively via the ANAS chatbot, amounting to 73.96%, while the remainder of calls required further action by a human operator.

In order to gain a more comprehensive view of the interactions, a thematic analysis was also carried out using T-LAB, resulting in the identification of four significant thematic clusters representing the content of the textual corpus. Each cluster consists of a group of elementary settings and is defined by the most characteristic words associated with the units of each setting. According to Rastier *et al*. (2002), the results of this analysis can be associated with an isotopy map, where each cluster, representing a specific theme, is characterised by the co-occurrence of semantic features. The analysis was carried out through an unsupervised clustering process, using a bottom-up approach. Each cluster, representing a thematic dimension, occupied a specific spatial dimension on the Cartesian plane (MCA plot in *Fig. 3*)[7], allowing the visualisation of proximity and distance relationships (similarities and differences) between the relevant elements. This geometric representation helped identify the specific vocabularies relative to each thematic cluster and understand how closely related or distinct the different themes were.

The first dimension identified in the analysis was "Reminders", which includes requests for updates on previously reported issues that have not yet been resolved. The analysis revealed that reminders often contain specific keywords related to urgency and immediacy, indicating that users were seeking quick and accurate answers. Moreover, terms like "files" and "images" are

[7] Words are presented on the Cartesian axis in Italian, as the textual material was originally collected in this language.

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also contained in the vocabulary, suggesting that this type of communication is sometimes supported by the attachment of digital material. This function, however, is made possible by digital contact channels, which cannot be applied in the case of telephone conversations and this thematic dimension underscores the importance of the chatbot’s ability to provide new and updated information to meet the users’ needs.

The second dimension, “Reports, Requests, and Interventions”, features interactions where users report issues, request assistance, or seek action to be taken. This category includes a wide range of user concerns, from reporting potholes, damaged signage, or road obstructions to requesting emergency services or roadside assistance. The analysis of this dimension highlights a need for the chatbot to be well-versed in information about service providers, emergency contacts, and procedures for dealing with various roadside issues. The vocabulary of this dimension is particularly focused on problem identification and resolution, emphasising terms related to defects, damage and requests for immediate action.

“Payments” has emerged as the third dimension, focusing on financial transactions related to road use, such as toll payments, fines, and other fees. Conversations in this dimension often include queries about payment methods, toll booth locations, payment deadlines, and procedures for appealing fines and highlights the need for the chatbot to provide clear and concise information about payment options and procedures, to make sure that users have a straightforward experience when dealing with the financial aspects of road use.

The final dimension, “Traffic Conditions”, covers conversations concerning the state of the road network, including real-time traffic flows, congestion levels, and alternative routes. Users often engage with the chatbot to obtain updates on traffic congestion, roadworks, accidents, and other factors capable of impacting travel time and route selection. This dimension suggests that the chatbot should be integrated with live traffic monitoring systems and offer route optimisation features to assist users in planning their journeys more effectively. It also highlights the importance of predictive analytics to anticipate potential traffic problems and provide pre-emptive advice.

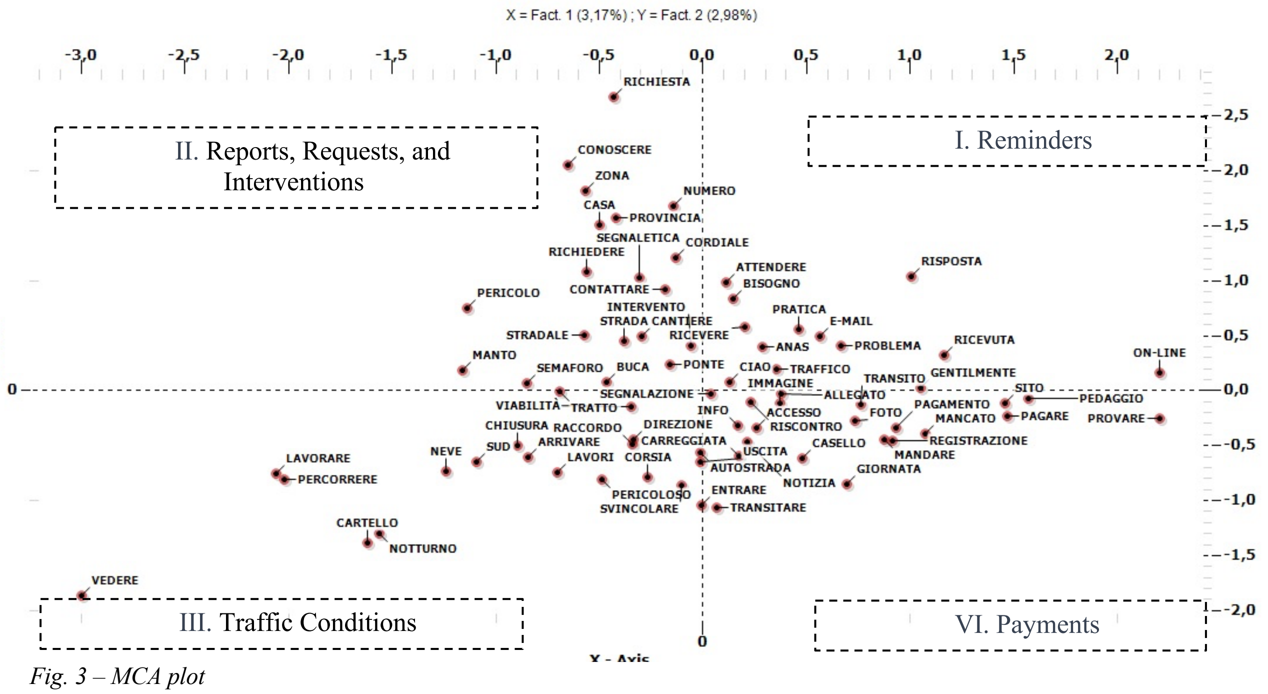

Fig. 3 – MCA plot

Moreover, studying the tone of voice adopted by users, through sentiment analysis, was considered another useful tool for detecting user mood, while also determining how engaging or

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distant the interaction with the chatbot was perceived to be. Therefore, this in-depth analysis was carried out to understand the general emotional trend of the interactions and to obtain valuable information about the satisfaction and overall experience of the users of the new digital channels introduced by ANAS. Data analysis (*Fig. 3*) shows that, in most cases (74.3%), use of the chatbot is devoid of any kind of emotional involvement, whether positive or negative. As a result, it can be argued that users use WhatsApp and Telegram in a purely instrumental manner, which underlines how the ANAS chatbot is not perceived as being able to engage in a friendly or empathetic conversation but is seen as capable of providing practical support only.

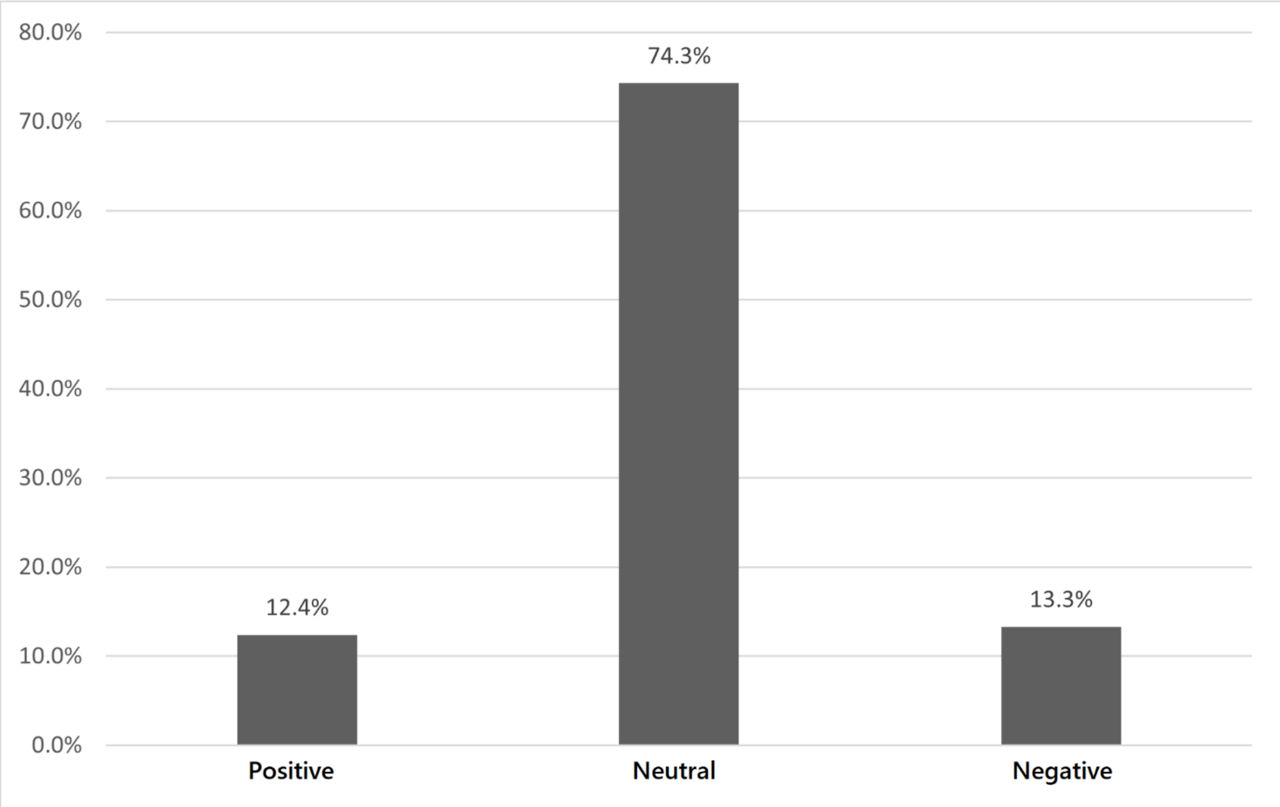

Fig. 3 – Sentiment Analysis

5. Discussion and Conclusions

The analytical approach adopted in the study has allowed us to acquire a deeper understanding of the nature and quality of interactions between ANAS chatbot users and the company and gaining a clear and detailed insight into the user expectations and experience, beyond a mere superficial appreciation. The analysis has revealed a greater preference for WhatsApp compared to Telegram, which reflects the general preference of most Italians with regard to messaging platforms. Recent statistics, in fact, confirm that 89% of Italians use WhatsApp compared to 36% who use Telegram (Audicom, 2023). Furthermore, 40.5% of Italians indicate WhatsApp as their favorite messaging app compared to only 5% for Telegram.

More generally, the data analysis has highlighted the overall effectiveness of the ANAS chatbot in handling interactions with users. The high percentage of communications managed/resolved by the chatbot indicates that this tool is able to deal with a significant volume of requests, even in time slots not usually dedicated to requesting information or sending suggestions or complaints. This enables the company to employ customer service staff members in more complex tasks, freeing them from having to engage in conversations that can be handled instead in an automated manner. This capability can be seen as a key element of the organisation's operational efficiency, allowing for the better allocation of human resources and faster management of user requests. Likewise, conversations

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taking place through WhatsApp and Telegram differ from those using other channels (such as call centres) in that users can attach and send pictures, videos or other files to improve understanding and resolution of requests. This feature can be particularly useful in situations where visual or attached documentation is essential to properly assess a situation or report.

The analysis also reveals circumstances that require further action by ANAS to improve the user experience. In particular, almost half of user interactions end abruptly, before completion, which could lead to more work for ANAS personnel, who are required to verify the nature of the interruption even in the conversations that are completed. To better understand the nature of these interruptions, it would be desirable to carry out an in-depth analysis of the causes, followed by the implementation of targeted improvements. Interrupted conversations can be caused by inaccurate answers, the chatbot's failure to understand the context, or difficulties in interpreting the user's requests. Furthermore, the hermeneutic analysis of the conversations showed that the structure of options and choices within the chatbot's decision tree may not be clear enough for users. Ambiguity within the options can lead to ineffective interactions, requiring subsequent intervention by operators, as users may not be able to easily find the answer to their requests. The recommendation is to design more streamlined and intuitive chatbots, combining similar possibilities and reducing the options where possible, to prevent users from experiencing frustration when the virtual operator does not appear particularly friendly towards them (Luo *et al*., 2022). As already highlighted by other studies on this topic (Ashfaq *et al*., 2020), when interactions with the chatbot appear tiring or difficult the user starts desiring to interact with another human being, underestimating the potential offered by AI.

Another element that can have a negative impact on user satisfaction is the chatbot's lack of historical memory. In fact, users have to provide some some information and consent before starting the conversation, even if they have already interacted previously through the same contact channel. As this process can also be demotivating for users, it could be useful to put into place a more efficient consent management system. For example, allowing users to give their consent once and then keep it for future interactions, unless the user decides to withdraw their consent (Kraus *et al*., 2023). Another way of addressing this critical issue could be to introduce the possibility of qualified access for users. This strategy would allow people to continue a conversation without having to start a new session each time. This would be particularly useful for complex interactions or requests that require multiple steps. Qualified access, together with an integrated system between the different communication channels and the CRM of ANAS, would allow the chatbot to archive and retrieve previous user conversations, facilitating the context and allowing for more tailored assistance.

Yet another critical point to consider is that the chatbot is unable to verify whether the road of interest falls under the jurisdiction of ANAS. It would be advisable to incorporate some AI-based solutions that could facilitate automated checks, allowing the chatbot to provide users with more accurate and relevant information regarding their concerns. This improvement would not only increase user confidence in the system, but also optimise the allocation of resources within the road management system. Furthermore, by leveraging artificial intelligence, predictive analytics can be implemented to anticipate potential issues based on various parameters, further refining the chatbot's capabilities and ensuring a seamless user experience.

Finally, the data analysis has also highlighted minimal emotional engagement by users. Specifically, chatbot conversations tend to be predominantly instrumental and neutral, devoid of emotion. This may affect the users' perception of ANAS in general. Several studies have already shown that a more engaging interaction with chatbots can improve trust, user satisfaction and their positive attitude towards businesses and organisations (Araujo, 2018; Chung *et al*., 2020; De Visser *et al*., 2016; Verhagen *et al*., 2014). Chatbot agents need to be developed in a way that also creates an emotional connection with customers, since the relationship is one-to-one. The advances being made in the field of automation can be a valuable asset in implementing more customised and engaging responses by the ANAS chatbot. For example, depending on the register of communication used by the interlocutor, the chatbot could assess whether it is appropriate to respond with more informal communication or use emoticons to add a touch of empathy and friendliness to the

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interaction. After all, the most satisfying experiences are those where users feel that they are chatting with friends or people who are pleasant to interact with (Kaptein *et al*., 2015; Lee & Choi, 2017). The public increasingly expects chatbot agents to be likeable, as well as knowledgeable and cooperative, showing empathy, compassion, care, and even humour (Neff & Nagy, 2015).

In conclusion, it is safe to say that modelling, profiling, analysing and understanding users is becoming increasingly important in many industries, also thanks to the support of artificial intelligence, and is a key to success in today's data-driven world (Corbisiero *et al*., 2022; Haddad *et al*., 2014). This consideration applies regardless of the business sector in which each company operates. The results obtained from the analysis of the interactions between users and the ANAS chatbot show that, in this case too, the conversational material is characterised by being a valuable source of information for better understanding the needs of the audience and, at the same time, for improving its customer service. Understanding users, their profile, key issues and desires can help companies customise their services and adapt strategies from the bottom up. This knowledge of users' needs can be used to increase their satisfaction, help them find the right answer more quickly and easily, and – as has already been done – identify aspects to integrated and/or modified for a more effective and efficient communication channel that responds to users' needs. In addition to the content, the form of the conversations can be another area for improvement. In this sense, important practical implications emerged from the data for AI designers and corporate communication professionals working in ANAS. The organisation could use the chatbot service more strategically, adopting a more dialogue-based style of communication, in order to maintain high-quality relationships with its users.

6. Limitations and future research directions

A major limitation of the study was the lack of context accompanying the conversations. In particular, it was not possible to fully evaluate the relationship between users and the ANAS chatbot, since no information was available about the users' situation before and after the chat. The database did not contain information on the users' history, so the researchers were not aware of any previous contacts with ANAS through other contact channels, or whether, for example, the users continued to seek information or have called the contact centre after the conversation with the virtual operator had ended. This is additional information that would have helped to understand how well the chatbot provided the right answer. Therefore, it would be desirable to track users over time and across different interaction channels to create an integrated analytics model. This model could include users' different interactions with the different contact channels to understand the chatbot's strengths and weaknesses from a comparative perspective. The analysis could also be enriched by integrating explicit user feedback. For example, the use of a Likert scale at the end of the conversation can give users the opportunity to evaluate their experience and satisfaction with the chatbot, on a scale of 1 to 5 or 1 to 10 (Akhtar *et al*., 2019).

Finally, future analyses could also consider some user characteristics for the adoption and perception of the chatbot. For example, a study that considers customer demographics such as age, income, status, lifestyle and education could provide further insights.

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