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AI as an organizational agent to nurture: effectively introducing chatbots in public entities

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ABSTRACT
We investigate how AI introduction affects public entities at the micro-level, hence the roles, competences and tasks of the agents involved. In doing so, we rely on the organizational design theory and we focus on a specific AI solution (chatbot) implemented within a defined microstructure, the customer service department. Using data collected through six exploratory case studies, we show how the creation of an AI team becomes a novel form of organizing that solves the universal problems of organizing. Results confirm that AI implementation is a complex organizational challenge and suggest that artificial agents act similarly to human ones.

KEYWORDS Artificial intelligence; public organizations; augmentation; automation; microstructure

Introduction

Artificial Intelligence (AI) refers to machines that can perform cognitive tasks that are usually associated to humans (Nilsson 1971), to support and increase decision-making and problem-solving activities (Androutsopoulou et al. 2019).

AI is not a new technological trend and, after gaining and losing popularity over the years (von Krogh 2018), nowadays it seems to have the potential to radically change many industries (Raisch and Krakowski 2021), among which the public one (Wirtz, Weyerer, and Geyer 2019). Within this industry, the focus on organizational challenges, in particular at the micro-level, appears extremely relevant (Raisch and Krakowski 2021). In fact, AI is an agent capable of action, it ingests large datasets, learning and taking decisions from them. Hence, it can support or even replace several public employees in their decision-making (Shrestha, Ben-Menahem, and von Krogh 2019), enabling novel forms of organizing.

Moreover, AI interacts with the environment, evolving *with* it (Agarwal 2018). Artificial agents, like human ones, are adaptive and able to change their outputs by learning processes (Dickinson and Yates 2021). These characteristics not only call for a redefinition of the division of labour between humans and machines (Choudhary et al. 2021) but also, and more broadly, for a complete rethinking of organizational processes, culture and relations affected by AI – especially in public settings (Mergel, Edelmann, and Haug 2019).

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Therefore, we define the following research question: *How does AI introduction affect public microstructures?* To answer this question, we first adopt as theoretical lens the organizational design theory and, more specifically, the microstructural perspective proposed by Puranam (2018). According to the author, every team, department, division and even the whole organization can be considered as a collection of smaller, simpler, and recurring patterns of microstructures, which are characterized by agents – not necessarily humans – with identifiable boundaries and system level goals that are reached through a proper division of labour and effective integration of efforts. The selection of this framework is based on Kretschmer and Khashabi (2020), who already showed its suitability to deepen the impacts of digital technologies on the functioning of organizations.

Then, we select as empirical setting of the study a specific AI solution, chatbot, adopted within a certain microstructure, the customer service department of public organization. According to previous studies (e.g. Misuraca and van Noordt 2020), chatbots are one of the most mature AI solutions across public boundaries. In fact, chatbots are intelligent systems able to manage large datasets and answer routine questions (Mehr 2017), features that appeared to be particularly valuable when considering public organizations. The customer service department is the microstructure that tend introducing chatbots and that is highly affected by these AI solutions. As a matter of fact, their introduction redesigns this microstructure, affecting how humans and AI interact and, ultimately, the whole organizational functioning.

Our results provide both theoretical and managerial insights. First, we demonstrate that AI becomes an organizational agent. Hence, it is important to investigate its interaction with other organizational members. Second, we observe that, to overcome the issues associated with AI introduction, a public microstructure implements a set of solutions that solve the universal problems of organizing proposed by Puranam, Alexy, and Reitzig (2014). The definition and implementation of these solutions lead to the creation of a novel microstructure, composed of both human and artificial agents – the AI team. Finally, we propose an actionable model to suggest how this team should work, pointing out which are the organizational agents involved and how their tasks and competences are re-designed and managed.

Literature Review

AI and chatbot adoption in the public sector

Applications using AI in public settings appeared more than a decade ago (Sousa et al. 2019). However, only recently the topic gained momentum (Dwivedi et al. 2021), due to a more mature technology (Sun and Medaglia 2019). This brought to a shift in the public sector, resulting in more applications developed and adopted (Misuraca, van Noordt, and Boukli 2020) but, above all, the widespread awareness that AI will fundamentally change public management (Berryhill et al. 2019; OECD 2019). Scholars and practitioners are aware that AI will cause a shift from an internet-based to an AI-augmented information society where public entities potentially can play a pivotal role (Ahn and Chen 2020).

Public organizations started adopting different types of AI (Wirtz, Weyerer, and Geyer 2019) in several areas, such as surveillance, law enforcement and service delivery. Consequently, setting the boundaries of *how* and *where* AI can be implemented in the public domain is extremely difficult.

Misuraca, van Noordt, and Boukli (2020) identified different applications in European public organizations, showing that AI is mainly adopted in public service delivery. However, and surprisingly, scholars in public management rarely investigated the topic (Kankanhalli, Charalabidis, and Mellouli 2019; Sousa et al. 2019), especially through empirical research (Dwivedi et al. 2021). In addition, how automated technologies transform the work of public organizations is rather an unexplored theme (Andersson, Hallin, and Ivory 2022), as current papers have mainly three focuses: AI types of applications (e.g. Ahn and Chen 2020), AI challenges (e.g. Wirtz, Weyerer, and Geyer 2019) and the expected impacts of AI implementation (e.g. Sun and Medaglia 2019). Moreover, scholars stress the importance of data quality and data integration both as essential preconditions for AI implementation (Wirtz and Müller 2018; Dwivedi et al. 2021) and for improving tasks performance (von Krogh 2018).

Ahn and Chen (2020) identify nine different AI applications, from resource allocation to sensors and autonomous driving. Among them, the authors include chatbots, which we have chosen as the empirical focus of this paper. Chatbots are intelligent agents able to detect and understand a spoken language, through text or speech, and use speech communication as a user interface (Androutsopoulou et al. 2019).

Chatbots are one of the most researched (van Noordt, and Misuraca 2019) and widespread AI applications among private and public organizations (Misuraca, van Noordt, and Boukli 2020). Chatbots' expectancies are to help public institutions in their daily relations with citizens and firms on reducing the administrative burden and increasing the quality of the communication channels (Androutsopoulou et al. 2019). However, Androutsopoulou et al. (2019) state that these promises have no longer been fulfilled and, nowadays, chatbots have been adopted not for radically changing service delivery, while for improving information seeking, allowing citizens to ask simple information, hence avoiding more complex research in government websites.

Androutsopoulou et al. (2019) state that, even with simple functionalities, chatbots create a more intelligent digital channel of communication, allowing public organizations to better reach a wide range of users.

Organizational challenges of AI introduction

The consequences associated with the introduction of digital technologies in organizational settings are among the focuses of a recent literature stream on digital transformation (Lanzolla, Gianv et al. 2020) also in the public domain (Nograšek and Vintar 2014; Tangi et al. 2020). In the public sector, literature on digital transformation emphasizes the complex cultural, organizational and relational changes to be tackled (Mergel, Edelmann, and Haug 2019) as well as the profound impacts on processes, people, culture and structures (Curtis 2019).

Considering these premises, the topic of digital transformation becomes particularly interesting when intersected with AI. Scholars highlight that its introduction is becoming, above all, an organizational challenge (Wirtz and Müller 2018; Raisch and Krakowski 2021), but the most discussed organizational consequence is workforce replacement (Sun and Medaglia 2019). Even if workforce replacement is the subject of relevant debate (Dickinson and Yates 2021), it has no longer been revealed in public organizations, making scholars state that this transformation is at least not imminent (Dwivedi et al. 2021), despite it causes considerable fear among employees (van Noordt, and Misuraca 2020a).

Moreover, the actual impacts of AI introduction must be addressed with a broader spectrum of elements, which range from the role of the management (van Noordt, and Misuraca 2020a), to the design of mixed teams of humans and machines (Puranam 2018), to the concepts of automation and augmentation (Raisch and Krakowski 2021; Veale and Brass 2019) and the required shift in the organizational culture (van Noordt, and Misuraca 2020b).

With the introduction of intelligent systems, machines are no longer simple artefacts, while they become a new class of agents in the organization (Raisch and Krakowski 2021) and this poses novel organizational challenges for which traditional managerial and organizational solutions are inadequate (Wirtz and Müller 2018).

More precisely, AI points out the need of integrating the concept of automation with the concept of augmentation (Raisch and Krakowski 2021). While automation means that human tasks could be substituted with machine tasks, augmentation refers to a close collaboration between machines and humans for performing tasks (Veale and Brass 2019). The automation of processes and services is not a new theme for public organizations and it has been broadly deepened in the last decades. The concept of augmentation instead is new and it leads also to the creation of new tasks that humans have to carry out (Dickinson and Yates 2021).

The adoption of AI augmenting human labour is particularly relevant when applied to the public sector. Indeed, both public organizations' knowledge and the amount of diverse data (legislative, operational, etc.) they own need to be translated into inputs that AI can ingest (Androutsopoulou et al. 2019). Moreover, on the one hand public organizations have to deal with several ethical, legal and political problems; on the other hand, the actions and outputs of public employees mirror government programs or determine access to public rights and benefits (Lipsky 2010). Hence, AI contribution in carrying out these activities and delivering public services should be carefully evaluated and its adoption requires a strict collaboration with human judgment to interpret results and manage harder cases (Martinho-Truswell 2018; Veale and Brass 2019; Wirtz and Müller 2018).

If the concept of automation is easy to understand (Dwivedi et al. 2021), augmentation requires organizations to explore how to create a human-machine collaborative environment in which AI influence human behaviour and *vice versa*. Raisch and Krakowski (2021) state that, only by properly balancing automation and augmentation, organizations can virtuously introduce AI in their activities. This new configuration has firstly implications for the micro-level, requiring above all a cultural transformation, which must be shaped *in primis* by senior managers (van Noordt, and Misuraca 2020a). Together with this, also management practices and human tasks must be revised (Wirtz and Müller 2018; Janssen et al. 2020) along with a proper process of education and training of employees (Ahn and Chen 2021). These activities are extremely challenging, especially in the public sector, where resistance to change (Ashaye and Irani 2019) and bureaucratic culture (Meijer 2015) act as barriers, and where the cultural change driven by the introduction of digital technologies is far from being reached (Tangi et al. 2020).

Organization design theory: the theoretical lens for the analysis

To investigate how AI impacts the internal functioning of public bodies, we leverage on the organization design theory and, more specifically, on the microstructural approach proposed by Puranam (2018). According to this lens, organizations are complex structures and it could be difficult to deepen how they work by leveraging only on a unitary entity approach (Kretschmer and Khashabi 2020; Puranam 2018). An organization is a multi-agents system that operates with specific boundaries to reach a certain purpose towards which the constituent agents' actions are expected to contribute (Puranam, Alexy, and Reitzig 2014). In addition, the microstructural approach narrows down the focus from the complexity of organizations to a few universal problems, the division of labour and the integration of efforts, and to a few building blocks, the microstructures.

According to Puranam, Alexy, and Reitzig (2014), the division of labour regards the breakdown of organization's goal in sub-objectives and tasks (*task division*), which should be allocated to individual agents (*task allocation*). As illustrated in Table 1, *task division* regards the division of organizational objectives into tasks and sub-tasks, and it can be done through workflow diagrams, business process maps but also self-selection based on individual skills and motivations. *Task allocation* regards the problem of assigning the list of sub-tasks identified through task division to an individual or group of agents. This step could be done always using an instrument such as workflow diagrams and according to different mechanisms: by assigning clusters of similar tasks to the same agents (specialization), minimizing interdependence across individuals, increasing the diversity of tasks or assigning responsibility for tangible outputs.

The integration of effort requires instead the resolution of both cooperation and coordination problems (Gulati et al. 2005), hence motivating individuals' commitment (cooperation) and ensuring that agents involved have all the information needed (coordination). The former problem is defined as provision of rewards; the latter as provision of information. *Provision of rewards* concerns the issue that every agent has interests that may, or not, correspond to the organization's goals and each organization needs to find solutions to induce individuals to accomplish the allocated tasks. The traditional form of rewarding is monetary compensation, but also intrinsic motivations could be pursued. *Provision of information* simply means that organizations should provide to their agents the information required to perform tasks. Moreover, as tasks are frequently interconnected and should be coordinated, agents need also to know what the other members are doing. Traditional forms of information provision are documents, plans, grouping or face-to-face meetings.

According to Puranam, Alexy, and Reitzig (2014), these issues are universal while the solutions that organizations adopt to face them may vary. The microstructural approach to organization design puts these universal problems at the centre stage of research and suggests focusing on novel bundles of solutions enabled by digital technologies (Puranam 2018). In fact, digital technologies profoundly alter the way of answering to the universal problems of organizing (Kretschmer and Khashabi 2020), for instance through the affordances they provide of visualizing the global task architecture and allowing mass and virtual collaboration (Puranam, Alexy, and Reitzig 2014).

Table 1. The four universal problems of organizing.

Division of labour	Integration of effort
Task division: mapping of organizational objectives into tasks and sub-tasks	*Provision of information*: ensuring that every organizational agent has the information needed to perform his/her tasks
Task allocation: assigning the list of sub-tasks identified to individuals or a group of agents	*Provision of rewards*: providing inducements to organizational members

Research Methods

As our understanding of AI in public settings is still limited, it becomes crucial to gather data from those people that are facing the phenomenon under investigation (Gioia, Corley, and Hamilton 2013) 'within its real-life context' (Yin 2013, 13). Thus, due to the phenomenon-driven (Eisenhardt and Graebner 2007) nature of the research purpose, we performed a multiple, exploratory case study (Yin 2013).

Case selection

As a starting point for case selection, we used a database of 215 AI initiatives developed worldwide, between 2018 and 2020. The database has been developed within the research conducted by the Digital Agenda Observatory of Politecnico di Milano (for further information see Maragno et al. 2021), an applied think tank led by two of the authors of the paper.

Starting from the database, we selected multiple cases adopting a theoretical sampling (Eisenhardt 1989; Eisenhardt and Graebner 2007) based on the following criteria. First, we focused on the European context. European countries operate within the boundaries of common regulatory frameworks, strategies and values. Hence, within these boundaries, we can be sure that public organizations strive to achieve similar objectives, which is a necessary condition to verify that the form of organizing enabled by AI introduction is novel and generalizable (Puranam 2018).

Second, we decided to deepen chatbots, which are the most adopted AI solutions in public organizations, as the last European census (Misuraca and van Noordt 2020) as well as our database show. Hence, we extracted from our database only projects related to chatbots implementation, operating at least in a pilot testing phase. In addition, we selected projects developed by different levels of government, to guarantee a higher degree of heterogeneity of the results. The final sample resulted in 14 initiatives.

Finally, we contacted the project manager of each initiative, asking for her/his availability to be interviewed. The selection process ended with the identification of six cases, resumed in Table 2.

Case A is a central public organization that provides services for an area of more than 10 million inhabitants. In 2019, the authority has started the development of the chatbot, with a machine learning algorithm. The chatbot is operative since February 2021.

Case B is a large local public organization, covering an area of almost 2 million inhabitants. Referee started thinking about the development of a chatbot as a complementary solution for the website. Nowadays the chatbot operates 15,000 questions per day, answering also to voice requests.

Case C is a large local authority, serving a territory of around 17 million inhabitants. The chatbot implementation, realized thanks to a public-private partnership, was related to the Covid-19 pandemic and to the need of dealing with the growing number of inquiries related to the epidemic.

Table 2. Summary of cases.

		Case A	Case B	Case C[1]	Case D	Case E	Case F
Organizational characteristics	Geographical Area	Northern Europe	Central Europe	Southern Europa	Northeast Europe	Central Europe	Southern Europe
	Population addressed	Around 10 million	Around 2 million	Around 6 million	Around 2 million	Around 2 million	Around 31 thousand
	Surface (km^2)	Around 450,000	Around 410	Around 17,000	Around 64,500	Around 750	Around 178
	Level of government	Central authority	Local authority	Public hospital	Central authority	Local authority	Local authority
	# of employees	+ 2,000	+30,000	~ 1,000	~ 160	~ 75,000	~ 200
Project characteristics	Starting year	2019	2016	2020	2017	2018	2021
	Maturity level	Pilot project	Fully operative	Fully operative	Fully operative	Pilot project	Pilot project
	Service provided	Answer FAQ regarding property management and property register	Answer FAQ, provide information related to Covid-19 and search on the website	Answer questions regarding Covid-19 and provide a self-assessment of the Covid symptoms	Answer FAQ regarding the process of enterprise registration	Provision of standard information and search on the website	Answer FAQ regarding taxes, educational services and search on the website

Case D is a central government agency in a small country of around 2 million inhabitants. The chatbot was launched in 2018, with an initial involvement of a local supplier, aiming to support the interaction between the organization and businesses. Since then, it responded to over 22,000 questions by almost 4,000 stakeholders.

Case E is a large local authority, serving an area of almost 2 million inhabitants. The implementation of the AI-based solution is part of a research project developed with a university and started in 2019. The chatbot is now in the pilot testing phase.

Case F is a small local authority, serving an area of almost 31 thousand inhabitants. The chatbot was launched during the Covid-19 pandemic, thanks to a free trial offered by the provider. After the first lock-down, the administration decided to enlarge the solution, including the replies to questions related to taxes and education services. The chatbot went online at the beginning of May 2021 and it is now in a pilot testing phase.

Data collection

To limit potential biases (Eisenhardt and Graebner 2007) and gather stronger insights (Eisenhardt 1989), we relied on multiple sources of evidence. As summarized in Table 3, we drew on primary data, namely semi-structured interviews, and secondary data, such as reports and policy documents, online news articles, websites. Moreover, four chatbots were available and have been tested, thus gathering direct observations. Both primary and secondary data have been organized in a database (Yin 2013).

The primary data consisted of three rounds of semi-structured interviews (overall 24) with 18 different informants, conducted between September 2020 and October 2021. For the majority of cases, the first interview was with the manager supervising the introduction of chatbot. The choice to consider this referee as the first contact point follows Puranam (2018). In fact, the project manager is the figure, within each specific project, with the authority to decide how tasks need to be divided among agents, direct subordinates these tasks and resolve potential disputes arising. Hence, understanding how project managers approached chatbot introduction allows deepening the way in which the four universal problems of organizing have been solved.

First, we began the interviews by asking informants to briefly describe the project and to summarize the reasons and objectives behind chatbot implementation. These questions allowed us to identify the main features of each project, such as the services delivered, the functioning and the training process of the algorithm and the role of the stakeholders engaged in its implementation.

Data were simultaneously collected and analysed. This cyclical process allowed us to gather new information based on the evidence arose from previous interviews (Gioia et al. 2010) and, following where the informants led us, we adjusted the protocol during the research. Therefore, the research increasingly focused on how chatbot adoption was transforming the organizational design of public organizations and the duties of both managers and employees. After this first round of interviews (one for each project), to achieve a higher 'representativeness and consistency' (Corbin and Strauss 1990, 9) of the observations, we contacted the same project managers and also the public employees appointed to train the chatbot. The second and the third waves of

Table 3. Data sources.

Case	Primary data	Secondary data
A	• 2 interviews with the Head of the Innovation Team • 1 interview with the Chief Information Officer • 1 interview with the Digital Strategist • 2 interviews with the chatbot trainer	• Authority website • Online news-article
B	2 interviews with the project manager	• Authority digital agenda programme • Authority website • Online news-article • Direct observation: testing of the bot
C	1 interview with the project manager	• Online news-articles • Supplier website
D	• 2 interviews with the project manager • 4 interviews with the chatbot trainers	• Authority website • Online news-article • European Commission reports • Direct observation: testing of the bot
E	• 1 interview with the official of the ICT department involved in the project • 1 interview with the project manager • 2 interviews with the chatbot trainer	• Authority website • Online news-article • National policy document • Direct observation: testing of the bot
F	• 2 interviews with the project manager • 3 interviews with the chatbot trainers	• Authority website • Project report with statistical data • Direct observation: testing of the bot

interviews were more focused, deepening on (i) how humans work was changing, (ii) the way in which tasks were divided and allocated among agents, (iii) the expertise required to perform the new tasks as well as (iv) the main factors driving people to work with the machine.

Each interview lasted at least one hour, was conducted using online tools by two of the authors and was recorded and transcribed verbatim. The first two authors cross-checked data and shared their initial ideas (Bourgeois and Kathleen 1988). The rest of the research team critically reviewed the observations. This approach allowed maintaining a high-level perspective (Gioia, Corley, and Hamilton 2013).

Potential information bias was addressed in different ways. First, all informants have been assured of anonymity (Eisenhardt 1989). Second, informants with diverse perspectives and roles were considered (Ozcan and Eisenhardt 2009). Finally, the interviews were complemented with archival and observational data Bingham and Eisenhardt (2011).

Data analysis

The methodology adopted for data analysis followed a grounded theory approach (Glaser and Strauss 1967). According to the recommendations for multiple case study theory building, within- and cross-case analyses were performed (Eisenhardt 1989; Eisenhardt and Graebner 2007). We started by individually analysing the primary data, and triangulated these with secondary sources (Jick 1979). Then, adopting an inductive approach (Saldaña 2015), we coded the interviews to identify the preliminary concepts. We then moved to a cross-case search, using replication logic across cases and clustering codes together in second order

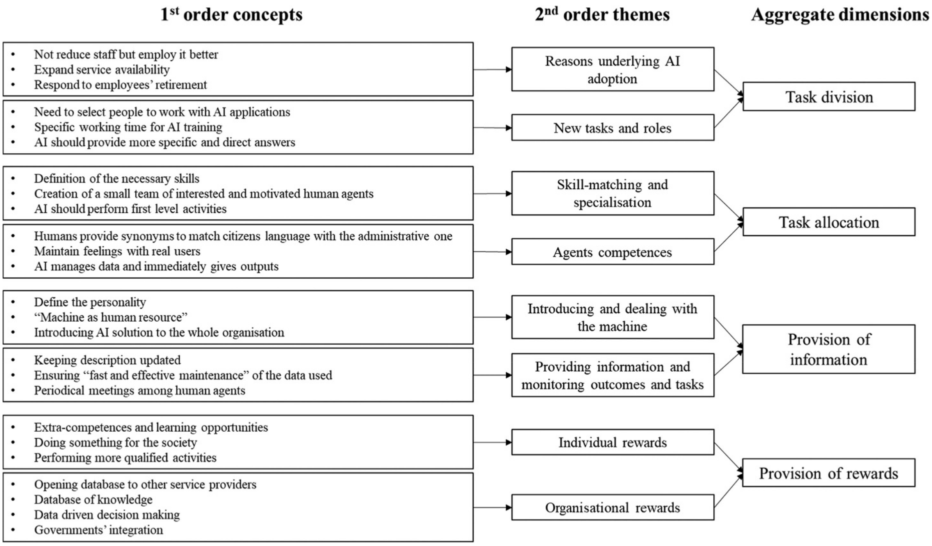

Figure 1. Data structure.

themes. As suggested by Gioia, Corley, and Hamilton (2013), if all the researchers did not completely agree, we revised the analysis until we reached a consensus and we then defined the aggregate dimensions.

Once the cross-case analysis was ongoing, we cycled between case data, emerging concepts and dimensions and the academic literature to refine the emerging construct definitions, abstraction levels, construct measures and theoretical relationships (Gilbert 2005). To show the process of data analysis and the evolution of conceptual categories (Suddaby 2006), the outputs of this phase are presented in Figure 1.

Findings

Research reveals that the introduction of AI affects the organizational design of public entities. Findings are reported in four paragraphs following the universal problems identified by Puranam, Alexy, and Reitzig (2014): task division, task allocation, provision of information, provision of rewards. Tables from 4 to 7 list representative quotes that supported in the identification of the solutions.

Task division

The first step in chatbot adoption was the identification of the reasons underlying its introduction. From the interviews it emerged that this choice was done to enhance service availability and support the internal functioning of the organizations. Indeed, as the project manager of case C noted:

> The bot offers 24-hour support to users, regardless of their geographical position and provides certain information.

And the project manager of case B pointed out how chatbot adoption enhanced efficiency and effectiveness in service delivery:

> Users can ask questions and receive an answer in five sentences, while on the website citizens have to read several paragraphs before finding the expected answer.

In addition, the project managers of cases E and F highlighted that the implementation of the chatbot is also a way to respond to a demographical change that is affecting public organizations: employees' retirement and the difficulties in replacing them. In the words of the project manager of case F:

> One of the key points in the choice to introduce the chatbot was that a lot of people are retiring, and we simply cannot replace them.

Finally, there was a consensus between all informants that chatbots would have allowed public managers to relieve civil servants from repetitive tasks. As the AI trainer of case E noted:

> Several questions we do receive are repetitive. For instance, often citizens call just to book an appointment with the authority. By introducing the chatbot, we aimed of relieving the employees from these routine tasks.

Hence, chatbots' application demands new roles, as the chatbot trainer of case A summarized:

> We have some goals within the organisation. One of them is to reduce unnecessary demands. With that in mind, we started taking the easy and frequently asked questions so the chatbot can answer them.

And the project manager of case D echoed:

> On the one hand, the job of the chatbot is to provide information so it could immediately indicate the desired direction to the customer. On the other hand, chatbot trainers assess the possibility to take over conversation from the chatbot, if the answer is too complex and the machine is not able to handle the situation.

AI introduction thus leads to demand for people that have to permanently change their duties, devoting at least a percentage of their working hours (if not their full-time activities) to train the machine. According to the interviewed chatbot trainers, this percentage varies from '10%' (case C) to almost 100% (case B). In all cases, it appeared that, to reach the final goal, it is necessary to create a team of few people – the AI trainers – with new tasks and positions. As reported by the project manager of case C:

> The need to create the team is also fundamental to get the result, otherwise it [= the implementation] can be counterproductive.

Comprehensively, Table 4 summarizes our findings, suggesting that:

> Proposition 1. AI introduction demands new tasks and roles, among which the most relevant is the algorithms' training. Human and the artificial agents have to perform different tasks, which are highly interdependent.

Table 4. Task division.

2nd order themes	Supporting quotes
Reasons underlying chatbot adoption	In the long term some employees might think: 'this chatbot could replace my work', but I don't believe so. As managers, we see it in a different way: we have so much to do and all our employees could have more qualified works that just answer these common questions. *Case A, Digital Strategist* We are more interested in cutting lead times actually. *Case A, Digital Strategist* Make the service available 24/7. *Case E, Project manager* The chatbot manages a notable flow of requests and allowed us to increase our responsiveness when performing other tasks. *Case C, Project manager* We introduced this chatbot not because we wanted to reduce our staff but because we have a lot to do and we need resources to do it better. *Case D, Project manager* It's great that the state institution can provide services also at other times: it's a new standard of availability for governments. *Case D, Project manager* Several questions we do receive are repetitive. For instance, often citizens call just to book an appointment with the authority. By introducing the chatbot, we aimed of relieving employees from these routine tasks. *Case E, Chatbot trainer* The bot offers 24-hour support to users, regardless of their geographical position and provides certain information. *Case C, Project manager* The aim is to increase the number of answers the organization provide to the users, even when the office is closed. Moreover, we should satisfy people's needs, hence it is essential to better understand which are the most asked topics. *Case F, Project manager* Users can ask questions and receive an answer in five sentences, while on the website citizens have to read several paragraphs before finding the expected answer. *Case B, Project manager* We do not intend to replace employees. We are facing a warring retiring period: we will have 20 to 30% employees leaving the organization because they have reached the corresponding age. We simply don't have enough capacity to replace those employees. *Case E, Project manager* One of the key points in the choice to introduce the chatbot was a lot of people are retiring and we cannot replace them. *Case F, Project manager* We just have a great chance to improve the service quality. *Case E, Chatbot trainer*
New tasks and roles	They are working also in the client service: they are using 80% of the time to train the chatbot and 20% to serve the clients. *Case D, Project manager* The need to create the team is also fundamental to get the result, otherwise it can be counterproductive. *Case C, Project manager* On the one hand, the job of the chatbot is to provide information so it could immediately indicate the desired direction to the customer. On the other hand, chatbot trainers assess the possibility to take over the conversation from the chatbot, if the answer is too complex and the machine is not able to handle the situation. *Case D, Project manager* We have some goals within the organization, one of them is to reduce unnecessary demands. With that in mind, we started taking the easy and frequently asked questions so the chatbot can answer them. *Case A, Chatbot trainer* On the one hand, the AI solution helps us to better understand the question and give more specific, more direct answers than before. On the other hand, we have to prepare and add the answers, writing them in a clear and simple way. *Case B, Project manager*

Task allocation

As depicted in Table 5, project managers assigned tasks to agents according to their respective features. On the one hand, AI should handle tasks that are repetitive, could be easily automated and that require the processing of a huge amount of data. As the project manager of case F described:

> We do not want to replace second level skills. The chatbot has to work on the first level, substituting humans in repetitive and low-value activities.

And the digital strategist of Case A added:

> [The chatbot] should understand what citizens are discussing and, then, translate the relative requests into answers that are not too complicated. It's rather complex because we, like any other public organisation, have our own weird "governmental language".

On the other hand, the allocation of tasks to humans follows two main criteria: matching duties with the skills already available within the organization and selecting high motivated employees. Regarding the latter, the project manager of case B stated:

> It's a story about patience. We are a small team and we take it personally if the bot does not provide the right answer.

And another project manager, the one of case D, echoed:

> I made a small team of five members. All of them are really inspired by this project and enthusiastic about taking part in the development of the solution. Team members are people open to understand what AI is and how it works.

Moreover, to reach the final goal, it is necessary a combination of humans and AI skills. For chatbots' training, all the informants stated that the limited knowledge of technical features was rather unproblematic, while the core competences are instead related to social skills and experience in relating with users through chatbots. As the project manager of case D affirmed:

> What citizens ask, which are their questions, how they ask these questions . . . all these elements are extremely relevant. You can't lose "human contact". Only starting from these, they [= the chatbot's trainers] are able to train the algorithm.

Cases showed that not only the ability in relating with users was fundamental, but also in-depth knowledge of the specific domain of the chatbot was needed for an effective AI introduction. As reported by one of the chatbot trainers of case D:

> We need to know very well all the elements, peculiarities and information of the institution where the virtual assistant is located. From the opening hours of the offices, to the possible ways for accessing a service together with all the exceptions that are processed differently.

Thus, in all cases the informants highlighted the importance of connecting citizens inquires, mainly frequently asked questions, to specific contents. As the chatbot trainer of case E described:

> If the chatbot is not able to provide an answer, we have to recognise the reasons behind it and make the "proper connections". For instance, we have to provide synonyms because, often, citizens use different words from the ones used in our institution.

This statement highlighted the importance to enhance a human-machine collaboration: when the chatbot was not able to manage certain inputs, the chatbot trainers complemented it with the required contents. This assertion showed also that, in order to enable a proper functioning of a chatbot, its trainers had to match citizens inputs with the language of the authority (Walton 2018). Public organizations have to overcome the bureaucratic language they are used to, for offering a communication channel that fit with users' conventions. In the words of the chatbot trainer of case F:

Table 5. Task allocation.

2nd order themes	Supporting quotes
Skill-matching and specialization	I made a small team of five members. All of them are really inspired by this project and enthusiastic about taking part in the development of the product. Team members are people open to understand what AI is and how it works. *Case D, Project manager* When we decided to introduce the chatbot, we had an exploratory meeting to understand which were the necessary skills. Once identified them, I created the team based on the competences we needed. *Case F, Project manager* Our manager asked if we wanted to be part of the project, if we have communication skills and also all those things that are needed for being an AI trainer. *Case A, Chatbot trainer* We do not want to replace second level skills: the chatbot works on the first level, substituting humans in repetitive and low-value activities. *Case F, Project manager* It's a story about patience. We are a small team and we take it personally if the bot does not provide the right answer. *Case B, Project manager* The chatbot should support people focusing on things that cannot be automated or that are not routine tasks: we really need people with a lot of knowledge and expertise to deal with those tasks. *Case E, Official of the ICT department* [The chatbot] should understand what citizens are discussing and, then, translate the relative requests into answers that are not too complicated. It's rather complex because we, like any other public organization, have our own weird 'governmental language'. *Case A, Digital Strategist* The chatbot has to interpret structured and unstructured data, which could be input as real-time data or updated after punctual reporting. *Case F, Chatbot trainer*

(*Continued*)

Table 5. (Continued).

2nd order themes	Supporting quotes
Agents competences	The customer service teaches us the right content so the bot can learn what are the most asked questions from our customers. *Case A, Chatbot trainer*
	We do have some kind of technological abilities: we are very IT affine, but most of us are not really technicians. *Case E, Official of the ICT department*
	I don't have any technical experience, but I think the most important thing is business expertise. *Case A, Chatbot trainer*
	It was easy to build the chatbot, but it was difficult to have good answers to the questions received by citizens. Technological development was simply the starting point. *Case B, Project manager*
	We need to know very well all the elements, peculiarities and information of the institution where the virtual assistant is located. From the opening hours of the offices, to the possible ways for accessing a service together with all the exceptions that are processed differently. *Case D, Chatbot trainer*
	Communication skills are crucial: we ask questions not in an administrative and technical language, but as a citizen who wants to have information. *Case F, Project manager*
	What citizens ask, which are their questions, how they ask these questions . . . all these elements are extremely relevant. You can't lose 'human contact'. Only starting from these, they [= the chatbot's trainers] are able to train the algorithm. *Case D, Project manager*
	We build the answer that we want the bot to write, then we test the training sentences that the bot will use to be trained. *Case A, Chatbot trainer*
	The knowledge of the services of which you want to give information is a necessary but not sufficient condition. Indeed, also the communicative perspective is crucial: as chatbot trainers, we have to adopt the point of view of citizens and use a language that is as clear as possible. *Case F, Chatbot trainer*
	We look at why the chatbot has not answered the customer's question. Then we search for a solution to avoid the error repetition. *Case D, Chatbot trainer*
	We bring together different people (doctors, specialists, virologists, responsible for relations with the public), to ensure that the questions could be balanced with respect to patients' expectations. *Case C, Project manager*
	The key point is to acquire good knowledge about the whole organization, its processes and also the different ways to provide services. *Case F, Chatbot trainer*
	If the chatbot is not able to provide an answer, we have to recognize the reasons behind it and make the 'proper connections'. For instance, we have to provide synonyms because, often, citizens use different words from the ones used in our institution. *Case E, Chatbot trainer*
	We look at all the questions for which we don't have any answer yet. Then, we make some statistics and look at the more frequently asked topics. Next, we make a list of priorities for incrementing the chatbots capacity starting from users' needs. *Case B, Project manager*

> The knowledge of the services of which you want to give information is a necessary but not sufficient condition. Indeed, also the communicative perspective is crucial: as chatbot trainers, we have to adopt the viewpoint of citizens and use a language that is as clear as possible.

Overall, the analysis of the interviews confirmed the findings of previous studies related to AI adoption in public organizations: the human competences related to technical features are not the only driver to accelerate chatbots introduction (Wirtz and Müller 2018); it is far away more crucial to develop and rely on the knowledge of internal experts (Raisch and Krakowski 2021) to capture and codify data that can be processed by AI, according to its specific technological features. Thus we concluded that:

> Proposition 2. Task allocation is accomplished according to skill-matching among human and artificial agents and following a specialisation criterion. AI takes over activities within its knowledge domain, which the AI trainers continuously update or correct.

Provision of information

Interviewed public managers described the organizational challenges associated with AI introduction and also the process of monitoring the tasks assigned to agents, as reported in Table 6. First, they focused on how they operated to prevent and overcome organizational resistance towards the chatbot. Referring to the digital strategy that guided the introduction of AI, the official of the ICT department of case E stated:

> I believe one major point characterising an effective digital strategy is not about technicalities. On the opposite, the organisational effort must focus on organisational mindset, processes reengineering, the culture of the employees and their attitude to digitalisation.

And the project manager of case C echoed:

> It is not possible to implement a chatbot without the involvement of all the business areas. This is a key element for the success of the solution: without the commitment of different departments there is a risk that the technology is misunderstood and, hence, obstructed.

Second, these attentions were also related to some features of AI, which are usually associated with human ones. Actually, as the Chief Information Officer of case A argued:

> The ability that AI has to learn from different fields, and act out of what it learned, makes it possible to talk about the bot in the same way as a human resource.

The informants recognized that these inherent characteristics of AI led public managers to approach the technology in a different way compared to other traditional technologies.

Third, considering the above-mentioned elements, public managers have to ensure that both the human and the artificial agents have the required information to individually perform their tasks and to combine them in order to reach the final output. As the project manager of case F noted:

> My role has a double nature: I have to encourage collaboration among colleagues but also coordination between all resources. The new inputs we provide to the chatbot, or those that are updated, must be in line with those of the counter, otherwise a misalignment would be created. It is a work of networking, of coordinating actions that will never end.

Empirical evidence revealed that this work of monitoring and coordination is done by leveraging on *face-to-face* communication channels among human resources (*i.e.* periodical meetings and reports) but also using platforms to revise data and supervise machine performances. As the head of the innovation team of case A noted:

> We have to control if the answers are out of our scope, if they solve – or not – user's demand. Within the office we have this chatbot panel. Through it, the [chatbot] trainers can interact with the machine, but we can also see how chat come in.

Finally, human agents gather and enrich the information to execute their actions also leveraging on the knowledge of artificial ones. In the word of the project manager of case D:

> Interestingly, we see that our new employees are chatting with the chatbot to acquire competences. Also our call centre uses the database of questions and answers to effectively train for addressing client requests.

Overall, the evidence suggests us:

> Proposition 3. Human agents have to continuously exchange data and information with the artificial ones, feeding the database that AI uses to perform its tasks and extracting information and knowledge from it.

Provision of rewards

The majority of the informants pointed out that the compensations they receive, while training and cooperating with the machine, are mainly non-monetary. In the words of chatbot trainer of case A:

> I worked in the customer service before and now I am within the innovation team: for me it has been a big and qualifying change. That's really good: I learn new things, techniques and I always do something different. I think this is a valuable reward.

This intrinsic motivation is a *leitmotif* among the different organizations and only case D provides monetary compensation due to the increasing responsibilities of the employees. However, as the chatbot trainer of case D noted, advancement opportunities still have a crucial role:

> We have extra competences; the organisation offers us bigger salary. Working with the chatbot is like a career development opportunity within the department but also a chance to grow outside the customer department. For example our first chatbot trainer now works in our development department with IT projects.

Another important inducement that emerged is strictly connected with the nature and aim of public organizations, *i.e.* serve the society. As the project manager of case B highlighted:

> I have the feeling I am doing something for good, for people, for the whole society. This fuels my motivation for working in the public sector. It is my daily job to inform all the public and I am paid by the public, so this is my reward.

The reward distribution does not regard only the individuals, but the whole public organization. Indeed, empirical evidence highlighted that AI implementation enhances the availability of valuable data, as inputs, and their proper usage (von Krogh 2018). As the project manager of case D pointed out:

Table 6. Provision of information.

2^{nd} order themes	Supporting quotes
Introducing and dealing with the machine	In the beginning, it was very important to understand the personality of the chatbot and how it will answer. It was necessary to define if it will use a formal or informal language, with emojis and things like that. *Case D, Project manager*
	During chatbot implementation, different areas of the organization have been involved, to enhance the sense of belonging. This was extremely important: we are a complex organization and we, as managers, have to encourage the cooperation between different business areas to overcome the resistance. *Case A, Chief Innovation Officer*
	We need to talk to machine resources in the same way as with people. *Case A, Digital strategist*
	When introducing a technology like AI, it is important to consider the whole organization as united, even if you adopt it in just one single line, as the customer department. In this way, you can reflect benefits also on the other parts of the organization. *Case A, Chief Information Officer*
	In order to enhance the acceptance of the chatbot within the organization we set an advisory board to share the decisions related to the machine. By doing so, even if the innovation is directed to the customer service department, everyone knows the ideas underlying its adoption. *Case A, Chief Innovation Officer*
	I believe one major point that characterizes an effective digital strategy is not about technicalities. On the opposite, the organizational effort must focus on organizational mindset, processes reengineering, the culture of the employees and their attitude to digitalization. *Case E, Official of the ICT department*
	We took care from the beginning of how to make the chatbot accepted by the employees. Hence, we involved different colleagues in the development of the solution. For instance, we involved several colleagues in the identification of the name of the chatbot. People had the possibility to vote for the name. Thanks to this silly trick, together with others, we engaged employees in the development of the project. *Case D, Project manager*
	The ability that AI has to learn from different fields, and act out of what it learned, makes it possible to talk about the bot in the same way as a human resource. *Case A, Chief Information Officer*
	It is not possible to implement a chatbot without the involvement of all the business areas. This is a key element for the success of the solution: without the commitment of different departments there is a risk that the technology is misunderstood and, hence, obstructed. *Case C, Project manager*
	We need to train AI systems and see if they function properly. This is almost the same way in which you train new recruiting staff. *Case A, Chief Information Officer*
	It's like a living system: every change in the training data means that the system has to be further trained. *Case B, Project manager*
	The completeness of the service description and the quality of the descriptions must be improved and kept updated. Decision-makers must understand that the chatbot is a kind of business card for the administration. *Case E, Project manager*

(*Continued*)

Table 6. (Continued).

2nd order themes	Supporting quotes
Providing information and monitoring outcomes and tasks	We have to control if the answers are out of our scope, if they solve – or not – user's demand. Within the office we have this chatbot panel. Through it, the [chatbot] trainers can interact with the machine, but we can also see how many chats come in, when . . . . *Case A, Head of IT Department* Chatbot trainers are always informed about all news, we are not isolated from daily tasks. Indeed, we do not only create new content, but we also review chatbot conversations with customers to understand whether conversation scripts and keywords are working properly. It is necessary to communicate with other departments of the organization and also other State authorities to provide the best and up-to-date content. *Case D, Chatbot trainer* As a project manager, I have to ensure the fast and effective maintenance of the data sources used by the chatbot. *Case E, Project manager* My role has a double nature: I have to encourage collaboration between colleagues but also coordination between all resources. The new inputs we provide to the machine, or those that are updated, must be in tune with those of the counter, otherwise, a misalignment would be created. It is a work of networking, coordinating actions that will never end. *Case F, Project manager* Some months after we implemented the project, we made an audit to be sure that the chatbot was working according to the standard that we set. That was really important to evaluate the machine job. We repeat periodically this audit, to verify that new information is processed according to our settings. *Case D, Project manager* We have a dedicated platform, that we defined '*the knowledge base*': it provides us with every kind of information. By our choice, only the employees involved in chatbot implementation have access to this platform and they can add or modify data. *Case F, Project manager* We work together two and a half days a week, so every week we see each other and we find out where we are. It's very close teamwork. Then, once a month, we have a meeting with our management, like all the chiefs and so on: we talk about what we are doing, how we are working, what we would like to do but also if there is something for which we need help. *Case A, Chatbot trainer* Interestingly, we see that also our new employees are chatting with a chatbot to acquire competences. Also our call centre uses this database of questions and answers to effectively train for addressing client requests. *Case D, Project manager*

> What I see is also the growth of this database: all these questions and answers. It is really important. Our employees can change or retire, but this knowledge always stays within the institution.

All cases declared to use, or they are planning to in the near future, these databases to reach further outputs than the automation of the services provided by the customer service department. For instance, case A and case D pointed out the importance of making available this dataset to other public employees. In the words of the chatbot trainer of case A:

> In the long run, we want the bot to be able to teach to our near employees. It is not only for customers; it is also educating our new employees.

The chatbot trainer of case E, focusing instead on the relation between the growth of the database and the enhancement of the services, stated that:

> We use [it] to improve the service description, which is also beneficial for the government site or the telephone hot-line because they use the same database as the chatbot. So, as we improve the database, the other services benefit from data as well.

Moreover, also due to privacy issues, public organizations develop their own platforms to store and manage data. These efforts, on one hand, allow public organizations to enhance specific competence within the department, which is recognized as a centre of expertise among other public organizations. As the chatbot trainer of case A noted:

> The knowledge that we have developed is crucial. We are the first government in the nation that uses a bot implemented in our own building. This process required a lot of extra work, but it is also going to save precious time in the future, not only for us but also for other public organisations. In compliance with GDPR, we are more than open to share our knowledge. I think this is very exciting and also very special about us as civil servants.

On the other hand, the implementation of this own platform allows public organizations to move forward in data management. Regarding this point, case A, B, D and F are the most interesting cases: starting from the data gathered by chatbots, these authorities are working to enhance the data sharing among other organizations – both public and private – even if they have not contribute to the project. As the digital strategist of case A noted,

> We have planned to integrate these two governmental bots. If you ask our organisation issues related to tax government, the question should be automatically sent to them. Our bot will send to them user inquiries and *vice versa*. Actually we will have government integration on the bot level.

And the project manager of case B echoed:

> The main questions are: "*How could we connect these single bots to one big bot, like a mother-bot or federation of bots? How could we connect different machine learning systems to build one big? And how do we select and separate all the questions?*" With all the Covid-19 answers, we did not implement an extra chatbot, we included it in the existing one, also to help the society with only one channel.

This process is rather innovative and it has still to be totally implemented, because it requires not only an integration among services of different organizations, but also the development of a common language between governments. In the words of the project manager of case D:

Table 7. Provision of rewards.

2nd order themes	Supporting quotes
Individual rewards	We have extra competences, the organization offers us a bigger salary. Working with the chatbot is like a career development opportunity within the department but also a chance to grow outside the customer department. For example, our first chatbot trainer now works in our development department with IT projects. *Case D, Chatbot trainer* I worked in the customer service before and now I am within the innovation team: for me it has been a big and qualifying change. That's really good: I learn many new things, techniques and I always do something different. I think this is a valuable reward. *Case A, Chatbot trainer* I have the feeling I am doing something for good, for people, for the whole society. That fuels my motivation for working in the public sector. It is my daily job to inform all the public and I am paid by the public, so this is my reward. *Case B, Project Manager* We can use people that usually sit and answer the phone to do better things and the chatbot will take over their activities. We do not want to get rid of people, we want them to do other things, better things for us. So the reward should be in to do better and more qualified activities. *Case A, Head of IT department* The first reason that leads me to take part in this project was my curiosity: I really want to know how it works. The second motive regards instead the internal functioning of the organization: thanks to the chatbot we relieve employees from routine tasks and we also provide better services. *Case F, Project manager*
Organizational rewards	By using the chatbot, we gather more information than through the website: we know what customers are asking, we can categorize theirs requirements. Moreover, we see what the chatbot can answer or what cannot. The management seems to be more and more interested in this kind of business intelligence. *Case A, Digital Strategist* The main questions are: '*How could we connect these single bots to one big bot, like a mother-bot or federation of bots? How could we connect different machine learning systems to build one big? And how do we select and separate all the questions?*' With all the Covid-19 answers, we did not implement an extra chatbot, we included it in the existing one, also to help the society with only one channel. *Case B, Project manager* Thanks to the chatbot introduction we talk more about the machine that augments the actual businesses. Indeed, as managers, we can get better decisions and we can allocate people to perform more complex matters. *Case A, Chief Information Officer* We achieved huge positive effects from this chatbot. We will always have this knowledge base within our organization. *Case D, Project manager* In the long run, we want the bot to be able to teach to our near employees. It is not only for customers; it is also educating our new employees. *Case A, Chatbot trainer* If you have your own platform, you can manage these inputs from the users. That is really interesting since you can extract more information out of it. *Case B, Project manager* We use [it] to improve the service description, which is also beneficial for the government site or the telephone hot-line because they use the same database as the chatbot. So, as we improve the database, the other services benefit from data as well. *Case E, Chatbot trainer* The knowledge that we have developed is crucial. We are the first government in the nation that uses a bot implemented in our own building. This process required a lot of extra work, but it is also going to save precious time in the future, not only for us but also for other public organizations. In compliance with GDPR, we are more than open in sharing our knowledge. I think this is very exciting and also very special about us as civil servants. *Case A, Chatbot trainer* What I see is also the growth of this database: all these questions and answers. It is really important. Our employees can change or retire, but this knowledge always stays within the institution. *Case D, Project manager* I would like to share the chatbot project also with other municipalities. We all provide the same services and citizens ask for the same needs. It would be useful to optimize data and knowledge. *Case F, Project manager* The problem we are solving with other institutions is how the chatbots of various governments can communicate between them and share their databases. *Case D, Project manager* We have planned to integrate these two governmental bots. If you ask to our organization issues related to the tax government, the question should be automatically sent to them. Our bot will send to them users inquiries and *vice versa*. Actually, we will have government integration on the bot level. *Case A, Digital Strategist* I believe that in the future maybe we can make our knowledge base accessible also to private firms. *Case D, Project manager* This is a very big challenge: how to manage those databases – because there are some keywords that all institutions have – and how to redirect users' to the right institution following these keywords. *Case D, Project manager*

> This is a very big challenge: how to manage those databases – because there are some keywords that all institutions have – and how to redirect users' to the right institution following these keywords.

In line with this, the project manager of case F stated:

> I would like to share the chatbot project also with other municipalities. We all provide the same services and citizens ask for the same needs. It would be useful to optimise data and knowledge.

The path that these cases are following shows that chatbot adoption could have broader impacts than the automation of specific services, but also than the augmentation in narrow domains. Overall, the evidence listed in Table 7 suggests us:

Proposition 4. Upskill, advancement opportunities, fulfilment of users' needs and reputational recognition prompt human agents to cooperate with artificial ones. The whole organization is rewarded by developing knowledge and data valuable for other public entities.

Discussion

Previous research suggests that AI is a fundamental organizational phenomenon (von Krogh 2018) and that examining the influence between humans and AI, as a hybrid organizational system (Raisch and Krakowski 2021), should provide valuable insights. However, empirical evidence in public settings is still weak. Addressing this gap, we examined how six public organizations across Europe have solved the four universal problems of organizing. The emergent solutions lead to the creation of a novel form of organizing: the AI team. A more fundamental contribution is a model of how this team, as a microstructure, works.

A set of solutions for AI adoption within public organizations

A primary contribution is the identification of how the customer service department designs its organization when introducing an AI solution. To investigate this topic, we considered the framework related to the universal problems of organizing (Puranam, Alexy, and Reitzig 2014; Puranam 2018). The solutions that the customer service departments undertake to solve the four problems of organizing lead to the creation of another microstructure – the AI team – where the chatbot is considered as an organizational agent, hence an entity capable of action (Puranam, Alexy, and Reitzig 2014; Puranam 2018).

First, the public managers interviewed focused on task division. Hence, they mapped the main goal of the microstructure – *i.e.* increasing quality, efficiency and effectiveness in the provision of a service through the implementation of AI – into a specific set of sub-tasks. The decomposition of the goal demanded the redesign of existing duties and positions, leading to the identification of new tasks, among which the most relevant is the AI training that demands a new role, the AI trainer. To accomplish the final goal, human and artificial agents have thus to carry out different but interdependent tasks (Proposition 1).

Further, moving to task allocation, it regards not only human agents, but also artificial ones. Indeed, according to their specific features, both agents could do what they are better at (Puranam 2021) and their outputs should be then combined to reach the final goal (Choudhary et al. 2021). Hence, on the one hand, the artificial agent should take over activities within the domains of knowledge for which it has been trained. On the other hand, the employees, becoming AI trainers, are relieved from old routine duties and will perform new and more qualified tasks, making AI competent and integrating the data that it ingests with in-depth and updated contents. This settlement requires a continuous interaction among AI and its trainer(s), which has to *work with* and *for* the machine. Moreover, algorithms' training requires specific competences and AI trainers should be carefully selected. Public managers assigned civil servants to certain sub-tasks, according to their skills and their personal interests (Proposition 2).

In our cases, information provision appeared to be a crucial aspect. AI has the capability to evolve with the environment (Agrawal, Gans, and Goldfarb 2018) and the digital transformation it brings is deeper rather than other technologies. For this reason, public managers had to create a common ground among the organization to make certain that employees to do not perceive the new agent as a threat. Next, human and artificial agents gather the information required to execute their respective actions thanks also to mechanisms of mutual learning. On one side, the artificial agent is fed with training data, which are characterized by human understanding of the environment; on the other side, the AI trainers learn from observing and managing the data gathered by the artificial agent (Park and Puranam 2020).

Finally, public managers should undertake actions to coordinate agents' activities: periodically face-to-face meetings with AI trainers were held; while the continuous interaction and coordination among the groups of humans and the artificial agent were feasible thanks to a dedicated monitoring platform (Proposition 3).

As regards the provision of rewards, the primary evidence is that the human agents cooperate with artificial ones for intrinsic motivations, identifying as main stimuli the importance to perform more qualified activities, enlarge their knowledge and advance their status. Public managers put themselves at the forefront of technological innovation and better fulfil their duty of offering high-quality services to the final users. Moreover, the reward distribution relates to the organization as a whole. First, the AI team is acknowledged among the other organizations – seen as departments of the same public entity or also other public organizations – as an expert domain area. Second, the six public organizations analysed, with the achievement of the AI team's goal, have started leveraging on data sharing and increasing collaboration processes with other public entities to enhance the quality of the services delivered (Proposition 4). Hence, due to the non-competitive nature of the public sector, also other organizations could benefit from the implementation of AI. This raises the question of why human agents contribute to the final goal. The evidence gathered reveals that informants value the possibility to share knowledge and data with other beneficiaries highly enough to perform their tasks, even if these organizations haven't contributed yet (Kenis and Raab 2020). Figure 2 resumes the abovementioned solutions.

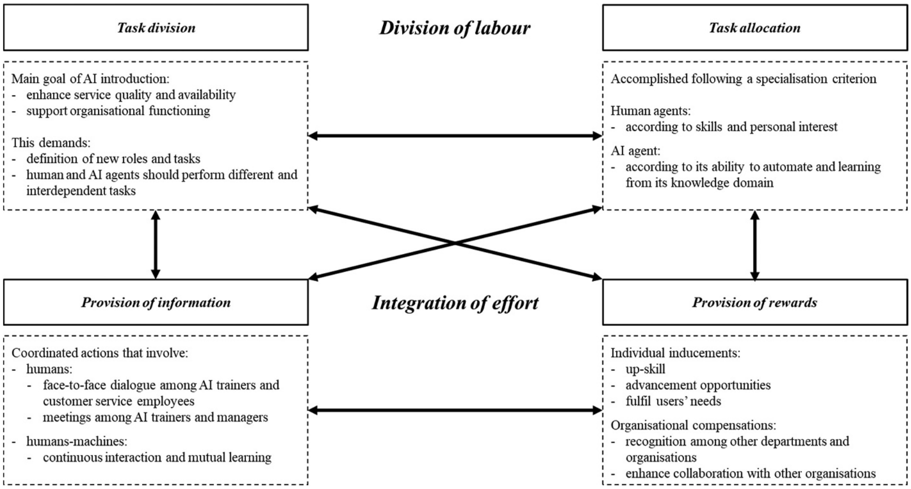

Figure 2. Customer service departments solutions for the four problems of organizing.

AI team as a novel form of organizing

Following Puranam (2018), the six public organizations have been compared to better understand the novelty of the solutions to the four universal problems of organizing.

As Table 8 depicts, all organizations have changed their existing forms of organizing to provide services with the support of AI. In particular, from the cases is evident how AI must be encoded differently within the organization: it is an agent capable of action with traits similar to the humans' one. This evidence has important consequences at micro-level, bringing to the need of designing the starting microstructures (the customer service department) differently. Indeed, through the introduction of AI, all cases solved the four universal problems of organizing adopting a common set of solutions that led to the creation of a new microstructure: the AI team. It is interesting to note that the creation of this microstructure is independent of the characteristics and the dimension of the organization. What differ is exclusively the size of the AI team in terms of the number of people involved or hours that people dedicated to this activity.

Table 8. AI trainers: number of people and time allocated to the training of the chatbot.

	A	B	C	D	E	F
# of AI trainer(s)	3	2	1	4	1	3
% of allocation per AI trainer	50%	100%	10%	80%	50%	15%

Our second contribution is a model of how the AI team, as a microstructure, works. The AI team is composed of three agents that must continuously cooperate and interact for accomplishing the specific goal: the AI solution, the AI trainer and the public manager Figure 3. Moreover, the system must be open to its external environment.

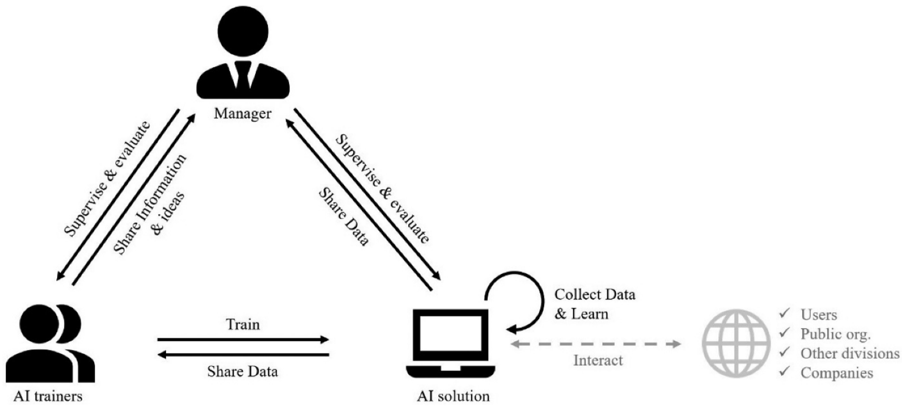

Figure 3. AI team as a novel form of organizing.

Each agent has a set of specific tasks and competences characterizing his/her/its work (Table 9).

The first step is to consider AI as an organizational agent, with its own competences and tasks. AI, in our cases chatbots, is able to process quickly a large amount of data (Janssen et al. 2020) learning from them and autonomously identifying the best way to compute a defined, delimited task.

Prior research, when looking at AI implementation, focused on competence and task disruption (Dwivedi et al. 2021) and the related managerial issues (Wirtz and Müller 2018). On the opposite, our research sheds light on a new role, which can represent the future of at least part of the actual job in the front office of public organizations: the AI trainer.

AI does not learn autonomously, while people have to spend time training and interacting with it. As showed in our cases, these employees do not need peculiar technical competence or background: AI trainers are people with skills closely related to the specific domains of AI implementation. In the case of chatbots, this means

Table 9. Tasks and competences of the AI team.

AI team member	Tasks	Competences
AI solution	• Automate first-line activities • Collect and elaborate data • Interact with external actors with a proper language	• Learn from the data collected • Generate new data • Translate from the bureaucratic language to the ecosystem(s) language
AI trainer	• Train the AI solution, ensuring the fitness with the ecosystem(s) • Updating the contents of the AI solution	• Deep knowledge of the business domain and ecosystem(s) mechanisms • Communication competences
Manager	• Define the goal beyond AI introduction • Allocate tasks according to agents' features and skills • Coordinate human and AI resources • Judge the performance of the machine • Provide motivations to AI trainers to enhance their cooperation with AI solution	• Knowledge of human resources and of their competences • Understanding of AI distinctive features • Usage of data to support decision making

involving people with social and communication expertise, working in customer service. Further, the human agents interact with artificial ones to create and stabilize over time the new models required.

This evidence support a remark on the debated trade-off between the concepts of automation and augmentation, and its relevance when looking at the organizational challenges, in particular the microstructural changes. Our empirical evidence pointed out that the establishment of an AI team could allow overcoming this dichotomy, as suggested by Raisch and Krakowski (2021). AI acts *in place of* (automation) and *with* public servants (augmentation), but also requires public servants *working for it*. In doing so, the role of the AI trainer is essential. Thus, AI implementation brings both automation and augmentation: a proper AI team is the way through which paradoxically establishing a virtuous cycle between the opposing forces.

Moreover, considering AI solution as an organizational agent highlights the need for a cultural change and contrasts with the fact that nowadays, in the public sector, organizational culture has been little affected by the introduction of digital technologies (Tangi et al. 2020). This shift calls for a change in the role of public managers, which play a pivotal role in properly introducing AI. As our findings reveal, public managers have firstly to create a common ground – *i.e.* 'knowledge that is shared and known to be shared' (Puranam, Alexy, and Reitzig 2014, 22) – to enable AI introduction; then, they should coordinate and evaluate agents' performances, ensuring that both humans and artificial ones have the information required to perform their tasks. With the support of human and machine resources, public managers can better fulfil users' needs and they can also leverage on the data gathered by AI for further analyses.

Finally, the AI team must be open to the external environment. Some interviewees were dreaming of a national chatbot, which collects data from the chatbots of all the central and local public organizations and can answer every question related to public affairs. This solution is certainly too futuristic, also for the accomplishment of privacy issues, but it has a necessary precondition: data sharing. In the case of chatbots, the system collects data from AI trainers and users. Making these data available to other public organizations would allow them to accelerate the learning process of their chatbots, recognizing if the question received was directed to the proper organization, and eventually automatically redirect it to the correct chatbot. These characteristics appear to be distinctive of the public sector. Due to the competitive dynamics, private companies are reluctant in sharing data while in the public domain different organizations could benefit from the accomplishment of the objectives of other public entities.

Conclusion

From a theoretical perspective, the main contribution of this study is the identification of a set of novel solutions that the analysed six cases designed to solve the four universal problems of organizing (Puranam, Alexy, and Reitzig 2014; Puranam 2018) while introducing AI.

This set of new solutions lead to the creation of a novel form of organizing: the AI team. This is a multi-agent system (AI solution, AI trainers, public managers) with specific boundaries (the ones of the customer service department) and a specific goal (enhance service delivery through chatbot adoption) towards which all the abovementioned agents have to contribute (Puranam 2018). Hence, the AI team is a new microstructure that co-exists within the customer service department which, in turn, is a microstructure in the broad public organization.

Our findings allow the possibility to make some more generalizable reflections that can be applied also in different AI solutions and related microstructures. As a matter of fact, the new microstructure, the AI team, is an organizational solution for generalist AI features, like the need of data, the need of training the machine and the importance of supervising the work done by the artificial agent. Hence we believe that this solution can be translated to different AI types. Moreover, the theoretical lens adopted, the microstructural approach, permits the recursion and the scaling of the specific solutions, linking the micro to the macro-structure.

Then, to deepen the design of the AI team, we focused on the interactions between its agents. Overall, the model depicts *who* are the organizational agents involved in AI adoption and *how* the novel microstructure works (Puranam, Alexy, and Reitzig 2014; Puranam 2018). Our last insight regards the automation-augmentation paradox (Raisch and Krakowski 2021). The novel microstructure – the AI team – demands for a mutual human-machine interaction and interdependence, where each agent supports and complements the work of the other.

This research is relevant also for public practitioners, providing them insights on the duties of organizational agents and an actionable model for AI implementation within a certain microstructure.

We are aware of several limitations and large room for further research in this direction. First, by adopting a microstructural approach we were able to gather insights on a certain public microstructure. It would be interesting to test our findings also in others.

Second, the research finds its empirical ground in a specific AI solution, chatbot. It would be valuable to apply the analysis to a broader sample of AI solutions. Third, we limit on cases in Europe while further studies should look at other geographical and regulatory domains.

Finally, we did not explore the evolution over time of the novel microstructure designed to solve the problems arisen with AI introduction. The solutions to the universal problems of organizing are not perfect nor permanent (Puranam 2018). The monitoring of the AI team over time could be a meaningful path for future research.

Note

1. For this case we considered as geographical area and user base the region where the hospital is located. However, the public hospital could offer services across the nation.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Data availability statement

The database of 215 AI initiatives that support the findings of this study is available from the corresponding author upon reasonable request.

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