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Text analytics for co-creation in public sector organizations: a literature review-based research framework

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Abstract

The public sector faces considerable challenges that stem from increasing external and internal demands, the need for diverse and complex services, and citizens' lack of satisfaction and trust in public sector organisations (PSOs). An alternative to traditional public service delivery is the co-creation of public services. Data analytics has been fueled by the availability of immense amounts of data, including textual data, and techniques to analyze data, so it has immense potential to foster data-driven solutions for the public sector. In the paper, we systematically review the existing literature on the application of Text Analytics (TA) techniques on textual data that can support public service co-creation. In this review, we identify the TA techniques, the public services and the co-creation phase they support, as well as envisioned public values for the stakeholder groups. On the basis of the analysis, we develop a Research Framework that helps to structure the TA-enabled co-creation process in PSOs, increases awareness among public sector organizations and stakeholders on the significant potential of TA in creating value, and provides scholars with some avenues for further research.

Keywords Text analytics · Natural language processing · Public services · Co-creation · Literature review

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1 Introduction

The public sector is experiencing major challenges due to the citizens' lack of satisfaction and trust in public administrations, the growing complexity of public services, as well as insufficient resources to respond accordingly (Rodriguez Müller et al. 2021; Torfing et al. 2016). One way to address these challenges is through the involvement of citizens in the development and production of public services, i.e., *co-creation*. Co-creation is not a new concept. Ostrom et al., (1978) used the term to explain the role of citizens in the production of public services. Its increasing popularity represents a move away from the New Public Management (NPM) paradigm towards a Public Service Logic (PSL) perspective in public administration management (Osborne 2018). As Osborne points out: "*PSL, therefore, starts from the service user as its basic unit of analysis and explores how public services and PSOs [Public Sector Organizations] might be designed to facilitate the co-creation of value by service users, not vice versa, [...] the potential to dramatically reconstruct how we conceptualize and govern the creation of value through the delivery of public services"* (Osborne 2018) (p. 229).

The use of digital technologies is assumed to increase different stakeholders' motivation to participate, promote mutual contribution, share perceived decision-making authority, and add to the potential public value of co-creation (Brandsen et al. 2018; Lember et al. 2019). Research has addressed the use of digital technologies in co-creation processes and the value they can help achieve. In addition, several case studies and best practices confirm that digital technologies can support co-creation across geographic, time and organizational barriers and provide interaction between service specialists and service users. Social media and digital platforms are frequently used for interaction and synchronous communication between public administrations and citizens because of their accessibility and participatory orientation (Chen et al. 2020a). Wang et al. (2022), for example, demonstrated how AI models could provide information for public service co-production, in particular during the planning phase, by analysing data collected from an online platform for residents' non-emergency requests for the delivery of city services. Manser Payne et al. (2021), present a value co-creation framework for AI services in the financial sector; whilst (Ali et al. 2022) develop a prototype for the delivery of services based on citizens' reviews of municipalities. However, the study by (Yang 2023) shows that AI service quality is key to the overall co-creation experience of citizens' use of AI, so attention should be paid to the design of the AI-supported services in order to avoid unnecessary negative experiences.

While co-creation and digital technologies contribute to public sector management, it is important to note that the focus of co-creation is not citizen engagement per se or the implementation of new digital tools. Public Sector Organisations (PSOs) must develop a participatory organizational culture that supports co-creation processes and the outcomes achieved. Such a participatory culture includes stakeholder cooperation and engagement, proactive use of government information and activities, and multiple formats of deliberation using different channels. As large amounts of online textual data are generated every minute on the web (World Economic Forum 2021), Text Analytics can be an additional technology that supports co-creation processes and outcomes (Rizun et al. 2023)

The challenge of extracting meaningful insights and knowledge from structured data and unstructured texts began in the 1980–1990 s (Frawley et al. 1992). Text Analytics (TA) originated in the 1940s with the development of Content Analysis, Computational Linguistics, and Natural Language Processing (Anandarajan et al. 2019). Since then, data and text mining have become increasingly popular. During the era of Big Data in the 2010s, a wide range of businesses extensively used corporate data, triggering the development of several TA solutions (Anandarajan et al. 2019). In comparison, the public sector has, in the past, rarely used TA (Munné 2016). However, the public sector has begun taking an interest in the use of TA applications to support public services, such as chatbots (Cortés-Cediel et al. 2023), public opinion analyses (Muktafin and Kusrini 2021), and expert systems (Avgerinos Loutsaris et al. 2021). TA is still in its early application stages in the public sector; nonetheless, it shows potential by identifying new services to be developed, the co-creation of outcomes such as public services, and thus improving service quality, increasing citizen trust and satisfaction with public services.

The limited application of TA in the development of public services highlights the need to understand further the role of citizens in the context of co-creation, how they interact with public services and PSO, and how they co-create value through text-based communication (Jacobs et al. 2018; Rodriguez Müller et al. 2021; Wood 2016) and AI-enabled function of public service (Yang 2023). Furthermore, it is important to explore the outcomes and effects of TA-based public service co-creation as well as the contributions digital technologies make to user satisfaction and trust, effectiveness of co-creation processes and service quality improvement (Ali et al. 2022; Rodriguez Müller et al. 2021). Our study *addresses the research gap* found in the literature on research and applications of TA in public sector co-creation. There is a clear lack of theory, structuring and standardization of co-creation in the context of TA and public service; thus, the following study *seeks* to present, in a structured way, current TA-related research in the public sector, the public value of TA in public sector co-creation, the potential of TA applications for co-creation, and to build the foundation for enhancing the use of TA in the process of co-creation in PSOs. We aim to fill this research gap by following two *research objectives* (O): O1: to conduct a *systematic review* of the literature on using TA in public services; O2: to develop a *research framework* for understanding the potential of TA in co-creation phases; O3: to identify *research gap*s in the studies on TA application for public service co-creation.

In order to reach the research objectives and develop the research framework, we set the following five research questions: RQ1: *How* can TA provide support in the public services co-creation process? RQ2: *Where* can TA provide co-creation support? RQ3: *When* can TA provide support? RQ4: *Who* can be involved in the design, development, and implementation of TA for public service co-creation? RQ5: *What* potential public value can TA provide for public service?

Our study makes some important *contributions*. This study is the first one to propose and define the public value of TA. Thus, *first*, the results contribute *to* the emerging body of literature; *second*, they increase the awareness of using TA to support co-creation in the public sector; *third*, the study structures the TA-enabled public service co-creation process; *fourth*, the research framework promotes the integration of TA into all phases of public service co-creation; *fifth*, the results support policy-makers and public managers, as we provide valuable guidelines for the development of user-centered public services that include stakeholders' interests and values; and *lastly*, we point out potential future research on the application of TA in public sector organizations.

The rest of the paper is organized as follows: Sect. 2 provides the theoretical background necessary to understand the research subject. Section 3 discusses the research design and methodology, that led to the retrieval of a systematic collection of studies. Section 4 provides an overview of our findings. Section 5 presents a research framework for TA in public service co-creation. In Sect. 6, we provide some concluding remarks and make suggestions for further research.

2 Background

This section provides the background on the key concepts of the study, namely Text Analytics, types of TA techniques and applications in public services, (Sect. 2.1), and the co-creation of public services (Sect. 2.2).

2.1 Text analytics

During the last decades, the development of TA solutions has experienced a strong increase due to the immense generation of textual data and Information Systems' capabilities to analyze them. TA solutions aim to support textual data processing and interpretation while delivering faster and better-quality results (Ojo et al. 2024). Some of the most common techniques are machine learning applied to text, e.g., text summarization, classification, and clustering (Anandarajan et al. 2019), sentiment analysis (Liu 2012), topic modeling (Blei and Lafferty 2009), semantic approaches, such as ontologies and knowledge graphs (Medelyan et al. 2013), artificial neural networks such as word embedding models (Naseem et al. 2020), information extraction, and multilingual solutions (Tomáš and Tibor 2017).

The rapid adoption of Text Analytics techniques in public services is propelled by advancements in machine learning-based text *classification*, *clustering*, *summarization*, and *Latent Semantic Analysis* (LSA). These TA techniques are applied in various ways: text classification is used for analyzing citizens' complaints (Hariguna et al., 2022), clustering helps organize legal texts (Lachana et al. 2021), text summaries process citizens' feedback on key public service issues (Kowalski et al. 2017; Liu and Jumadinova 2019; Pan and Chen 2021), and LSA supports automated community feedback analysis (Obidallah et al. 2020; Sanjifa et al. 2019). For such ML-based models, ensuring explainability/interpretability remains crucial to maintaining public trust, as citizens need clarity on how automated decisions are made (Anagnostou et al. 2022). In the current stage, explainability methods are typically "general-purpose" with broad goals like perceived transparency, rather than addressing specific real-world needs. Furthermore, they are rarely rigorously evaluated for effectiveness in practical applications, with most research focusing on benchmark problems (Amarasinghe et al. 2023). Human supervision to mitigate risks of inaccuracies in automation remains necessary (Liu and Jumadinova 2019; Wu et al. 2021). Data preparation is another challenge, as public sector information frequently exists in non-machine-readable formats (e.g., PDFs, scanned files), risking errors, especially in the initial stages of information extraction (Kalampokis et al. 2023). Addressing bias, data privacy, and fairness is essential. ML-based models used must process data from diverse demographics without bias (Mac 2020), and handle personal data in compliance with privacy standards to protect citizens' information (Henman 2020; Pi 2021).

Sentiment analysis and *topic modeling* are popular TA techniques used, for example, to gather information about people's views on various subjects, events, and products, investigate creativity in marketing (Das et al. 2023a, b), detect fraud and security risks (Carmichael and Eaton 2023), in health coaching (Beinema et al. 2022), analyze student evaluation of teaching (Sun and Yan 2023), and monitor the public's attitude toward governmental crisis responses such as COVID-19 (W. Zhang et al. 2022a, b). In the public service context, sentiment analysis and topic modeling are established TA techniques used to analyze citizens' comments on social media (Iskandarli 2020), actively supported by ML- and Deep Learning-based models (Naseem et al. 2020; Wankhade et al. 2022). However, challenges persist, including ensuring contextual relevance in sentiment analysis, performance on low-resource-languages, overcoming interpretability issues, and achieving accurate topic labeling, especially for complex domains (Ignat et al. 2023; Konstantinidis et al. 2024). Additionally, these methods require robust data handling and balanced human oversight to mitigate biases, maintain data quality, and validate outputs effectively (Ojo and Rizun 2021; Peet et al. 2022). Data privacy and security pose significant challenges, as open digital platforms and social media data may contain personal information; and data transfer across networks risks unauthorized use and attacks. Additionally, context-specific social media data requires filtration and redundancy removal, with no standardized method for retrieval and automatic transformation for analysis (Verma 2022).

Semantic technologies, such as ontologies, knowledge graphs, and linked data, have become essential in enabling knowledge construction, understanding, and reuse across sectors, including the public sector (Gutierrez and Sequeda 2021). These tools serve as a backbone for constructing interoperable frameworks that improve data sharing and accessibility in areas like procurement systems (Soylu et al. 2020), air traffic management (Keller 2019), and parliamentary systems (Leskinen et al. 2022). Semantic Web technologies, such as ontologies, enable knowledge to be machine-readable, shared, and reused, which enhances interoperability and data integration across public organizations (Kalampokis et al. 2023). By creating common semantic data models, these technologies support unified reporting methods and the automation of processes based on knowledge from diverse sources. Furthermore, they promote transparency and openness in public sector services (Pucihar et al. 2007). However, challenges remain, including achieving seamless interoperability and managing the complexity of integrating heterogeneous data sources, which requires ongoing research and refinement of these tools to maximize their potential in public service applications (Antunes et al. 2024).

Chatbots are increasingly adopted across various public service areas, including health (Amiri and Karahanna 2022; Larsen and Følstad 2024; Wilson and Marasoiu 2022) or tourism (Cortés-Cediel et al. 2023; Zhang et al. 2022a, b), and as contact points in municipalities (Abbas et al. 2022; Følstad and Bjerkreim-Hanssen 2023). Their main applications include responding to citizen inquiries, addressing complaints, conducting document searches, directing individuals to the appropriate offices, performing translations, and assisting with document drafting (Anandarajan et al. 2019; Mehr et al. 2017; van Noordt and Misuraca 2019). Most public service chatbots, known as intent-based chatbots, facilitate information retrieval from a knowledge base, using AI to interpret user input and determine intent via natural language processing, and providing responses based on set rules (Luo et al. 2022). This approach integrates data-driven language processing with rule-based responses, ensuring reliable answers while allowing users to clarify or adjust their input if needed (Abbas et al. 2022). However, if the chatbot fails to recognize an intent or the request is out of scope, errors may occur (Verne et al. 2022). Chatbots in public services are also noted for fostering self-service and enhancing resource efficiency (Makasi et al. 2022). However, limitations remain, with current chatbots often seen as too simplistic or focused on administrative goals rather than user needs (Androutsopoulou et al. 2019; Makasi et al. 2022). Generative AI chatbots like ChatGPT could potentially enhance interaction depth and response quality but are not yet deployed in public service use cases due to several challenges (Larsen and Følstad 2024). These challenges include issues commonly associated with chatbot technology, such as accuracy, transparency, and limited explainability. Additionally, there are growing concerns about fairness, potential bias, abuse in data interchange, and compliance with regulatory standards. To retain the benefits of LLMs while mitigating risks, public administrations are recommended to consider strategies such as developing proprietary models, fine-tuning models on specific data, and running them locally for better data control (Council of the European Union 2023). Additionally, using open-source and European models aligns LLMs with local regulations, while cooperative procurement structures and legislative oversight ensure ethical and effective implementation, helping reduce significant risks associated with high-stakes, public-facing applications (Al-kfairy et al. 2024; Skjuve et al. 2023). Beyond the proliferation of chatbot technology, its "physical counterpart", i.e., the humanoid robot, is also not as popular due to trust and ethical issues (van Pinxteren et al. 2019) as well as scarce research efforts in this area (Andreas et al. 2019; Budiharto et al. 2020).

2.2 Public service co-c

Co-creation is a concept originally developed by Ostrom et al. (1978), who introduced a model of public service production where the citizens influence objective community conditions and the public agency outputs. Co-creation is seen as improving public value in several ways, such as leading to higher service quality, expanding opportunities for participation and engagement, enhancing the quality of information provided by public administrations, and ensuring that citizens have greater satisfaction with public services (Cordella et al. 2018; Osborne et al. 2016). Local public sector organisations are increasingly recognizing the importance of involving citizens in the provision of social and welfare services, such as budget discussions, social housing projects, and support for young mothers (Meričkova et al. 2015; Torfing et al. 2019). The European Union also supports regional partnerships focused on stimulating rural growth and employment (Pattinson and Dahlöf 2019). Regional authorities have collaborated with private stakeholders to develop public transport, and urban development, and improve their internal and external environment quality (Rösler et al. 2021; Toukola et al. 2023). At the national level, public agencies are fostering networks of public and private actors to tackle issues like child welfare, elderly care, and climate policy (Matti et al. 2022; Røiseland 2023). At the same time, challenges arise as co-creation processes can expose gaps in citizens' understanding of public services, potentially limiting their ability to effectively evaluate policy options and innovative solutions. Co-creation may also generate excessive, complex, and low-quality information, impeding effective decision-making. Failure to adhere to ethical standards, unclear accountability procedures, and lack of transparency in the co-creation processes can undermine participants' willingness to engage in co-creation in the future (Edelmann and Mureddu 2023). These challenges highlight the need for citizen-centric governmental processes and institutions, along with adequate capacities, to foster active stakeholder involvement and ensure their effective integration into decision-making processes. Since citizens continue to heavily rely on analogue public services, co-creation in this domain commonly involves instruments, such as interviews, surveys, focus groups, and meetings. However, there is a growing trend among public sector organisations to enhance the scope of co-creation by incorporating digital tools and a combination of both (hybrid co-creation) (Rodriguez Müller et al. 2021).

Digitalizing public sector organizations supports co-creation, particularly for reaching vulnerable or hard-to-reach users (Jalonen et al. 2021). Digital tools are crucial for enabling online debates, collaboration, crowdsourcing, and organizing input to develop new public services (Edelmann and Mergel 2021). They empower users to actively participate in content creation, editing, and evaluation, making platforms like social media effective for citizen engagement (Chen et al. 2020b; Kaplan and Haenlein 2010). In the public sector, these tools facilitate innovative processes that deliver public value (Lember 2017). By supporting interaction across geographical and organizational boundaries, digital technologies – especially AI and text analytics – enhance the impact of co-creation (Ali et al. 2022). However, simply providing online platforms does not ensure effective engagement (Kreijns et al. 2003). Advancing digital co-creation requires a systemic approach that prioritizes aligning digital infrastructure with organizational structures (Jacobs et al. 2018; Rodriguez Müller et al. 2021); establishes strong data governance and acquisition frameworks (Bertot et al. 2010); allocates responsibilities among the co-creation actors (Hepburn 2018; Linders 2012); adheres to regulatory standards that ensure accountability, transparency, ethical integrity, and decision rights (European Commission 2021; Jobin et al. 2019; Vinuesa et al. 2020); and complies with policies and the ethical implications (Kankanhalli et al. 2019; Sousa et al. 2019).

Our study initiates this holistic approach by examining context, phases, and stakeholder dynamics to drive public value outcomes, supporting sustainable and trustworthy co-creation practices (Edelmann and Virkar 2023; Jacobs et al. 2018; Misuraca et al. 2020; Rodriguez Müller et al. 2021). We adopt the definition of co-creation as a *process by which public and private actors address a shared problem via a positive interchange of diverse types of information*, *resources*, *and skills* (Torfing et al. 2016). Additionally, we use Linders' (2012) cycle of co-creation in the context of public service, which includes *three phases*: co-design, co-delivery, and co-evaluation, along with the mechanisms that operationalize each phase. The *co-design* phase provides an essential frame for the conception and layout of the service that is to be designed and engages different stakeholders in the development of the specific public service. The *co-delivery* (or co-execution) enhances the acceptance of the services through the involvement of stakeholders in the delivery of the public service, by promoting communication between service providers and stakeholders and providing a more integrative user experience (Sicilia et al. 2016). The c*o-evaluation* phase, also known as co-assessment or co-monitoring (Rodriguez Müller et al. 2021), assesses the service after its delivery to learn from it or to adapt it through possible prospective elements in which lay actors and the government work together to assess service quality problems (Nabatchi et al. 2017). The use of the co-creation phases and mechanisms (see Appendix A.1) helps us organize and study the available literature as well as fulfilling the research objectives of the paper.

The literature also emphasizes the need for understanding the various *stakeholders* involved in and the values they can obtain through co-creation (Webster and Watson 2002). Two primary groups of stakeholders, *government agencies* and *citizens*, are prominently mentioned in the literature as they play a key role in public service co-creation, but there may be many more stakeholders, all with multiple needs (Nabatchi et al. 2017). In the context of e-government and digital transformation, stakeholders can include private sector companies (Rösler et al. 2021), IT service providers, civil servants, department heads and IT departments (Ashaye and Irani 2019). Ashaye and Irani (2019) also mention other stakeholders such as faith-based organizations, voluntary organizations, non-profit organizations, or academic institutions, The identification and analysis of the potential values are closely linked to the involvement of the stakeholders, that is, those individuals or groups having a vested interest or concern in the provision, quality, and impact of public services (Bassey et al. 2022; Janssen et al. 2017).

Public value is defined in various ways (Moore 2016; Williams and Shearer 2011), but there are only a few recommendations on how public value can be co-created (Scupola and Mergel 2022). In the digital government context, public value can be considered an outcome but also a by-product of investments in digitization; however, it is neither clear how digitization creates public value (Bannister and Connolly 2014) nor how it can be measured (Panagiotopoulos et al. 2019). In this study, the *public value of TA for public service* is defined as *stakeholders' expectations towards public service when its co-creation is supported by TA* (Twizeyimana and Andersson 2019). We build on a recent taxonomy of public values derived from research on co-production (Scupola and Mergel 2022): 1) *Economic Value* (V1), that is, the efficiency gains from applying text analytics (TA) to support public service co-creation, such as reduced government expenditure, decreased reliance on human resources, and overall increased efficiency; (2) *Citizen Value* (V2), the direct value individuals experience when TA supports citizen involvement in the co-creation process, for example, enhanced transparency, a reduction in administrative burdens, and an increase in the number of services delivered; (3) *Societal Value* (V3), the broader societal benefits provided by public services co-created with the support of TA and framed within legal regulations such as increased trust in the public sector, higher user satisfaction, and improved security; and finally, (4) *Administrative Value* (V4), when TA facilitates and improves co-creation outcomes such as better public service delivery, better regulations, streamlined communication, and personalized services.

3 Method

This section describes our approach to conduct an extensive literature review. We use the systematic literature review (SLR) and the content analysis method proposed by (Brous et al. 2020; Webster and Watson 2002). The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) (Moher et al. 2009) guidelines are utilized to conduct the SLR. In the next sections, we describe (1) study identification, (2) study selection, (3) data extraction, and (4) data synthesis of the relevant literature.

3.1 Search strategy

Five electronic databases were selected for the literature search: Scopus, Web of Science, ACM Digital Library, Springer, and IEEE. These databases were chosen as they are major bibliographic sources that focus on both social sciences and technology (Sousa et al. 2019; Zuiderwijk et al. 2021). *First*, three sets of search queries were used to refine the search strategy: (1) ("*Co-Creation*") AND ("*Public Service*")– to trace the trends in the development of the co-creation concept within public services; (2) ("*Natural Language Processing*" OR "*Text Analytics*" OR "*Text Mining*" OR "*Textual Data*") AND ("*Public Service*")– to explore the intensity of research development related to the application of NLP and TA techniques in the public sector; (3) ("*Natural Language Processing*" OR "*Text Analytics*" OR "*Text Mining*" OR "*Textual Data*") AND ("*Co-Creation*") AND (*"Public Service*")– to analyze the extent of research at the intersection of NLP and TA technologies, co-creation, and public service.

The results of this analysis are presented in Fig. 1 (after removing the duplicates and non-English studies). We can observe significant growth in studies applying NLP and TA techniques in the public sector since 2016, with a notable surge between 2019 and 2022. Additionally, starting in 2018, there has been a rapid increase in interest in co-creation approaches for public services. As represented by the green line in Fig. 1, there are several publications at the intersection of NLP and TA technologies, co-creation, and public service. Starting in 2019, the number of publications slightly increases by 2022.

Second, the results from the two search queries: (1) "*Natural Language Processing*" OR "*Text Analytics*" OR "*Text Mining*" OR "*Textual Data*") AND ("*Public Service*"); and (2) ("*Natural Language Processing*" OR "*Text Analytics*" OR "*Text Mining*" OR "*Textual Data*") AND ("*Co-Creation*") AND (*"Public Service*") were taken for further data collection and analysis. The analysis focused on publications from the period 2019–2022. In total, when using the two search queries and after removing duplicates and non-English studies, we collected 334 results from the five searched databases: Scopus (61 papers), Web of Science (11), ACM Digital Library (1), Springer (256), and IEEE (5). Given a limited number of papers explicitly mentioning public service co-creation or related contextual synonyms and TA concepts together, we included a broader range of studies in the search, from litera-

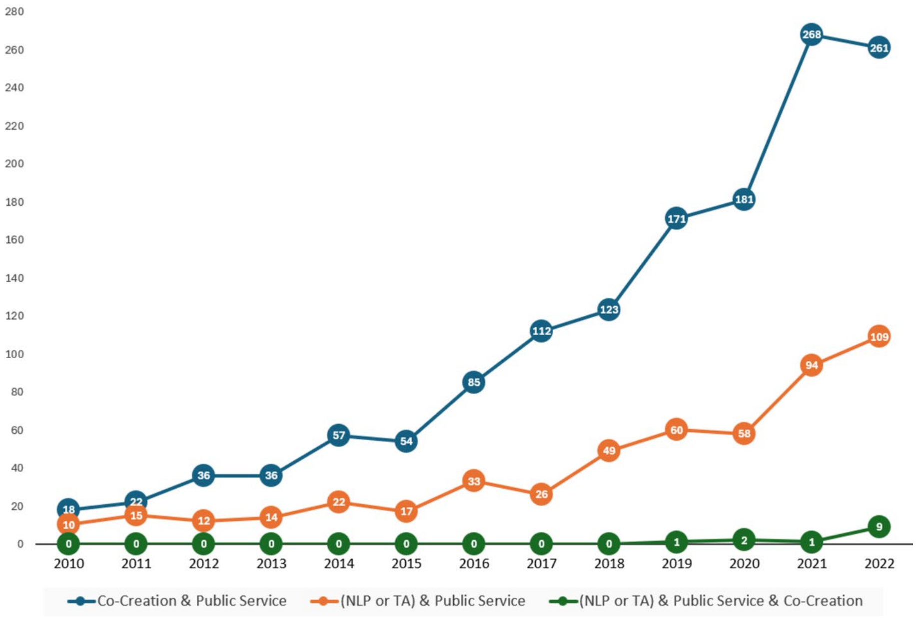

Fig. 1 Extended search queries results

ture reviews and overview papers to technical studies, conceptual papers, and short research or project reports.

3.2 Study selection

In this section, we describe the *inclusion* and *exclusion criteria* (Appendix A.2) designed to select papers from the initial set of papers collected during the literature search step. Using the cleaned set of 334 papers, we started with the identification of eligible publications, checking the title and abstract to assess the relevance and quality of the study. Three experts, i.e., academics with experience in research and consulting projects on text analytics, co-creation, and e-government, were involved in this analysis phase. Every title and abstract was independently examined by at least two experts (with 50% overlap of analyzed articles between expert pairs) to comply with the inclusion and exclusion criteria. Results from all three experts served as input for the subsequent pseudo-Delphi problem-solving process in cases of disagreement between the experts (Reddick et al. 2017). The Delphi process was organized as a structured iterative group communication process (sessions), supported by feedback on individual contributions and providing the experts with the opportunity to reconsider their views in order to achieve full agreement (Dalkey 1969; Okoli and Pawlowski 2004; Reddick et al. 2017). Cohen's Kappa measure was calculated to measure inter-coder reliability and identified values between 0.63 and 0.65 across all pairs of coders/experts. This led us to identify 86 full-text articles. *Third*, adopting a snowballing approach, we enhanced the search results. Among others, several earlier publications, from 2011 to 2014, were included in this step. *Finally*, 104 full-text papers were included in the eligibility assessment step. Due to the quality and relevance issues, another 29 articles were excluded. This resulted in 75 full-text studies for the quantitative synthesis (see PRISMA flow diagram in Appendix A.3). This relatively low number *highlights the scarcity* of research examining aspects of actual and potential applications of TA in public service co-creation.

3.3 Data extraction

To extract data from all included studies, we used a spreadsheet to record the metadata for each of the selected studies. The metadata from the 75 full-text selected studies included: descriptive information, approach-related information, text analytics techniques in a public service context and functionality addressed, stakeholders involved in the TA application, and the main benefits and challenges solved (values) by the TA application (Appendix A.4). The summary of publication characteristics, including publication country, and research method, is in Appendix A.5. To ensure the data extraction process quality, one of the experts extracted information from all included studies, and then the other two experts reviewed the extracted information. A pseudo-Delphi session was organized to achieve expert consensus. Identified values for Cohen's Kappa measure ranged from 0.58 (for Public values) to 0.70 (for TA functionalities) for all pairs of coders (see Appendix A.6 for more information on specific inter-rater reliability scores for each extracted data).

3.4 Data synthesis

The results obtained during data extraction allow us to develop a research framework. This framework systematically organizes the knowledge gained on existing and potential TA applications to support public service co-creation. To reach the research objectives and streamline the framework development, we set the following five research questions:

RQ1: *How* can TA provide support in the public services co-creation process?

RQ2: *Where* can TA provide co-creation support?

RQ3: *When* can TA provide support?

RQ4: *Who* can be involved in the design, development, and implementation of TA for public service co-creation?

RQ5: *What* potential public value can TA provide for public service?

The narrative synthesis approach (Bassey et al. 2022; Popay et al. 2006) was applied to the research framework development. Three independent experts iteratively analyzed and coded the raw data obtained in the previous steps. *First*, the identified TA techniques and their functionalities were grouped into categories (*RQ1*). *Second*, public service areas (*RQ2*) addressed in the studies were categorized. *Third*, in order to operationalise the adapted concept of co-creation of public services (see Appendix A.1) to the context of TA–enabled co-creation of public services, available cases of successful implementation of single service co-creation mechanisms in the public sector were selected and analysed. As a result, a *research model* (Table 1) was developed to map TA applications to co-creation phases and mechanisms (RQ3), grounded in the rules established for identifying the *theoretical potential of TA applications* in supporting the co-creation of public services.

Fourth, potential public service co-creation *stakeholders* (*RQ4*) were extracted from collected literature, coded, and grouped. *Fifth*, based on the raw data on the addressed problem, benefits, and challenges, the information about *potential public values* (which are either expected or actually achieved in the analyzed study) from the use of TA for public service co-creation (*RQ5*) was extracted, coded, grouped, and mapped to the co-creation *phases* and specific public service co-creation *stakeholders*.

The *consistency* of the results at the systematic synthesis stage was ensured by implementing the following research approach: (1) each expert performed the categorization/mapping procedure independently; (2) a pseudo-Delphi session was organized for experts to discuss the validity of the results obtained and the identified discrepancies; (3) during the pseudo-Delphi session, experts independently refined their results; (4) a further expert discussion was organized to guarantee the maximum consistency in results; (5) as a result, consensus was reached and the final results were approved by all experts. Cohen's Kappa measure was used to measure inter-coder reliability for each specific categorization/mapping procedure. The identified Cohen's Kappa values varied: (1) for the categorization procedure from 0.63 (for Public values) to 0.77 (for Public service areas); (1) for the mapping procedure from 0.50 (for TA techniques at the Co-delivery phase) to 0.75 (for Stakeholders). *Finally*, statistical processing and analysis of the systematic synthesis results were carried out and are presented in Sect. 4. The full summary of systematic literature review coding is presented in Github[1].

[1] *Systematic literature review summary.*

Table 1 Research model of aligning TA techniques to support public services co-creation phases and mechanisms

Co-creation Phase	TA application contextualization for co-creation mechanisms	Real cases of TA application scenarios
Co-design	**Consultation & ideation mechanism**: The TA technique enables *stakeholders* to participate in two-way communication between stakeholders and p*ublic administration* by (i) *sharing* their questions (ideas, suggestions or requests) regarding public services through digital platforms, official social media accounts and groups, or public service delivery systems, preferably equipped with question-answering systems (e.g., virtual assistants or chatbots); (ii) *making it easier* to provide answers to questions by eliminating time and geographical constraints; (iii) *receiving* instant clarifications or suggestions in text or voice form; and (iv) allowing to *view*, *support*, and *collaborate* on the *most relevant* comments from others. The TA technique enables *public administration agencies* (i) to be *responsive* by giving quick and direct answers to queries; (ii) to *collect* and *analyse* input from the public; thereby (iii) to *understand* users' needs, requirements and expectations; (iv) to provide the actionable *insights* from data analysis for public service *improvement* (e.g., to make the best selection from among various policy and service design alternatives); and (v) to be *transparent* by informing stakeholders about the process and results of their participation in public service co-design (e.g. via real-time dashboard) *Informing mechanism*: The TA technique enables *public administration agencies* to equip citizens with data needed to make informed decisions by (i) *extracting* information from various textual data sources (e.g., government documents and reports, stakeholders' and experts' opinions, public surveys, posts and comments on official social media accounts and groups, news), combining it with other data formats, including real-time data; (ii) *sharing* the results of data *analysis* (e.g., data clustering, classification, prediction, comparative analysis, association rules, and other pattern types) in an interpretable and explainable form; and thereby (iii) to *nudge (encourage)* a shift in *stakeholders'* mindset, positioning them as active co-designers of public services rather than passive users The TA technique enables *stakeholders* (i) to increase their *awareness* of various aspects of public services; and (ii) ensure *informed* and socially *responsible* decision-making (including at all phases of public services co-creation)	*MISSI* is a Mississippi chatbot that answers residents' questions about taxation, health services, public transport schedules, elderly care centers, social gatherings, tourism hotspots, and possible job opportunities. *Emma* is a computer-generated virtual assistant who can answer immigrants' questions and assists users with visa-related inquiries on the U.S. Citizenship and Immigration Services (USCIS) webpage. It answers a wide range of questions about immigration processes and visa applications, helping reduce human workload and providing accurate, up-to-date information. Emma is available on desktop and mobile and in both English and Spanish. *EngagementHQ* and *CitizenLab* are online platforms that optimize city planning and development projects by promoting online community participation and facilitating public consultation for local and central governments. CitizenLab platform keeps citizens informed of their participation process and outcomes by offering 24/7 access to clear insights through advanced dashboards. CitizenLab also provides community organizations and government officials with a digital toolkit to create and manage their own virtual consultation projects (Deamer, 2020). The *Text Mining and Analysis Competence Centre* of the European Commission's Joint Research Centre (JRC) conducts (i) text analytics of large volumes of online textual data, such as legislative texts and scientific articles, (ii) Europe Media Monitoring, and (iii) Political Intelligence to support EU policy-making. The results are shared with stakeholders to inform them of policy decisions and improve public understanding of policy implications. *GovText* is a platform for public officers to utilize Topic Modeling to analyze data from surveys and citizens' feedback, helping them discern primary topics and insights. Additionally, it offers a summarization feature to condense news articles, thus enabling faster reading.

Table 1 (continued)

Co-creation Phase	TA application contextualization for co-creation mechanisms	Real cases of TA application scenarios
Co-delivery	**Crowdsourcing mechanism**: The TA technique enables *public administration agencies* to delegate public service- relevant problems or activities to *stakeholders*, such as: (i) providing *consultations* to other stakeholders by writing constructive comments or responding to specific requests based on their personal experience and tapping into their unique skills, talents, and knowledge; (ii) *recommending* to participantsthe most relevant comments and responses that meet their requests; (iii) providing necessary *information* (in textual form) required to solve government challenges in real-time; and (iv) opening up a powerful *problem-solving mechanism* by using government online platforms, official social media accounts, or public forums for this purpose The TA technique enables *stakeholders* to: (i) become more deeply *involved* in citizen-to-government and citizen-to-citizen *interaction* and *collaboration*; (ii) be directly *engaged* in public service provision and real problem-solving; and (iii) enhance their *awareness* of various aspects of public services by leveraging citizen-based skills and expertise *Ecosystem embedding mechanism*: The TA technique enables *public administration agencies* to build and maintain a unique public service ecosystem environment for the wider public community, which benefits from the open sharing of public administration agents' knowledge, infrastructure, and other resources. TA's role here parallels the Consultation & Ideation, Crowdsourcing, or Informing Mechanisms approaches described above, but adjusted to *ecosystem embedding* and public services co-delivery context by, for example, enabling public administration: (i) providing *intellectual consultation* within an online community of practice, where public administration agents offer expert guidance and consultation to stakeholders; (ii) provision a *digital platform* for the transparent sharing and exchange of public data and resources; and (iii) assistance to *identify* and *correct* misunderstandings or misinterpretations in text-based forums. This TA technique enables *stakeholders* to: (i) increase their *awareness* of various aspects of public services by leveraging *public administrations agents*-based skills and expertise; (ii) become more deeply *involved* in citizen-to-government and citizen-to-citizen *interaction* and *collaboration; (ii) access to* openly sharing government knowledge, infrastructure, and other assets for use; and (iii) increase their *trust* in public administration.	*FixMyStreet* is the crowdsourcing platform that enables people in England, Scotland and Wales to identify, report and discuss local issues. It includes interactive maps to identify problems in particular UK areas, real-time monitoring of an extracted list of problems in specific areas, and channels for communicating these problems to the relevant respective council (Hallin, 2023; Sowmya & Pyarali, 2013). *FixMyTransport* is a free web service that enables citizens to report issues to the public transport system, such as inadequate facilities, overcrowding, delays, and fare problems, directly to local transport authorities. It is integrated with social media platforms such as Facebook and Twitter, gathers information from various public transport databases, and monitors in real-time recently reported problems. The reported concerns are passed on to the relevant local authorities and monitored for action (Aitamurto et al., 2016; Hallin, 2023). *Community Health Data Initiative* is an AI-based solution that enables small local community organizations, city agencies, and governments to join forces and identify health challenges, propose solutions, and involve all key stakeholders in a collaborative effort. TA is used for extracting insights from unstructured data.

Table 1 (continued)

Co-creation Phase	TA application contextualization for co-creation mechanisms	Real cases of TA application scenarios
Co-evaluation	**Citizen reporting mechanism**: The TA technique enables *stakeholders* (i) to provide *information* and *feedback*, offering either appreciation for actions taken by public administrations or other citizens, or reporting issues related to public service quality; (ii) *making it easier* to provide this information eliminating time and location constraints; and (iii) allowing to *view*, *support*, and *collaborate* on the *most relevant* information from others; by using for this purpose government reporting platforms, electronic surveys, official social media accounts and groups, preferably equipped with question-answering systems (virtual assistants or chatbots) The TA technique enables the *public administration agencies* (i) to *collect* and *analyse* the input from the public; (ii) to *identify* the determinants and measure the users' satisfaction; (iii) *prioritize* actions for public service improvement; thereby (iv) to produce rigorous *evidence* for policy making and monitoring; and (v) to be *transparent* by informing stakeholders about the results of public services evaluation (e.g. via real-time dashboard) *Open book government mechanism*: The TA technique enables *public administration agencies* to (i) *build* datasets from various public service-related textual data sources, combining them with other data formats; (ii) *proactively disseminate* these datasets as open government data, making them available for public scrutiny and reuse; (iii) provide easy *access* and intelligent *search* functionalities (e.g., through virtual assistants or chatbots); (iv) present information in an *interpretable* and *explainable* form (e.g., via dashboards); and (v) ensure *transparency* by informing stakeholders about the inner workings and performance of public administrations. The TA technique enables *stakeholders* to (i) gain *deeper insights* into how public administrations operate and perform; (ii) make *informed* personal decisions; (iii) be empowered to hold public administrations *accountable*; and (iv) increase their *trust* in public administration.	*NHS Choices*, *Patient Opinion*, and *iWantGreatCare* are UK Healthcare public services where patients can leave feedback and rate their experience with a general practitioner (GP) service, hospital, dentists, and other healthcare services. Collected data is processed by LDA. *GOV.UK* is an open feedback link 'Is there anything wrong with this page?' on an UK governmental platform, and can detect significant changes in the demand for a service. The collected data is processed by LDA and sentiment analysis techniques The *Singapore Municipal Services Office* (MSO) is a chatbot on social media platforms (WhatsApp and Telegram) that (i) automatically categorizes complaints by their nature; (ii) extracts incident details; and (iii) determines the appropriate government agency the case has to be forwarded to (*GovText– The Whole-of-Government Text Analytics Platform| Singapore Government Developer Portal*, 2021) *Opendatabot* is a chatbot that provides information on Ukrainian open government data, including company registration, legal documents, and property ownership records. It enables users to search for specific information within open datasets and obtain relevant details. *Ask Izzy* is an Australian website that connects people in need with housing, meals, and financial help, provides support in case of family violence, counseling and other services. A new open data platform will help track the support services that people who are homeless or at risk are searching for and to better match services with actual needs. It includes a voice assistant (*Ask Izzy Open Data Platform to Uncover Homeless Need| Infoxchange (AU)*, 2016)

4 Results

In this section, we aim to answer the following two research questions: RQ1: *How can TA provide support in the public services co-creation process*? (Sect. 4.1–4.2) and RQ2: *Where can TA provide co-creation support?* (Sect. 4.3).

4.1 Text analytics techniques

We identify 28 standalone *TA techniques* that (1) are currently employed to analyze and understand unstructured text data in a public service context, and (2) can *potentially* support public service co-creation processes. These TA techniques were grouped into ten main categories (RQ1), although the majority of studies employ several TA technologies. Figure 2 provides an overview and distribution (number of publications where these TA techniques are mentioned) of TA technique categories. The most representative categories (around 77.14% of all TA techniques) are *Machine learning-based* techniques (20.00%), such as text summarization, classification, clustering, association rules, and LSA; *Sentiment analysis* (18.10%), including lexicon-based and machine learning approaches; *Chatbot* (17.14%), based on machine learning and deep-learning models; *Topic modeling* (12.38%), such as LDA and STM; and *Semantic Web and Linked Data* (9.52%), such as Ontologies, Knowledge Graphs, Semantic Networks, Linked Data, SNA. The remaining category of TA techniques (22.85%) is *Information Extraction* (6.67%), which includes methods like Named Entity Recognition (NER) or keyword matching. Additionally, *Artificial Neural Networks*, encompassing Deep Learning and Embedding models, and *Humanoid Robots*, which involve speech recognition and generation, account for 5.71% and 2.86% respectively. It is noteworthy that despite the significant potential and advancements in state-of-the-art TA methods, some studies still rely on manual or rule-based approaches, represented by the *Content Analysis* category (5.71%), which includes techniques like discourse analysis, thematic analysis, and rule-based matching. Interestingly, these approaches are more common

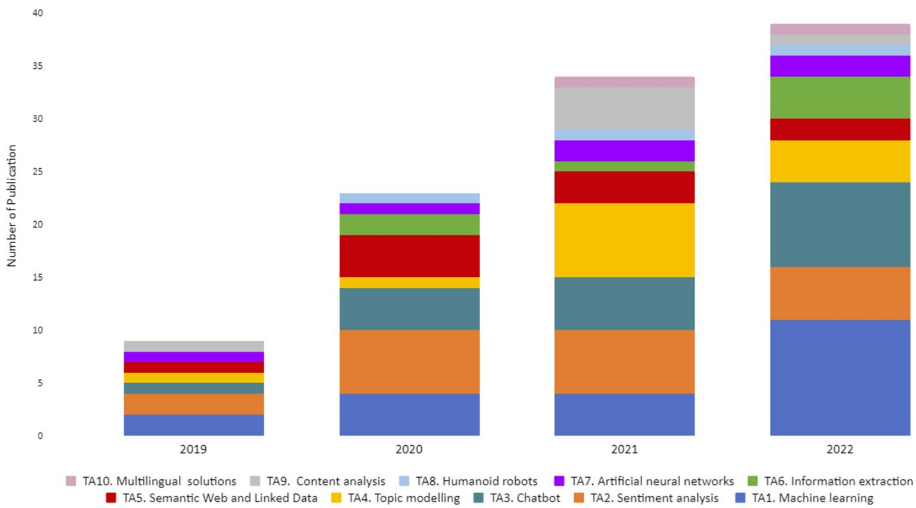

Fig. 2 Categories of TA techniques in public services (RQ1)

than *Multilingual Solutions* (1.90%), which include machine translation and multilingual Natural Language (NL) generation.

We also observe the development trends of the main TA categories over time. *Chatbot* popularity has steadily and consistently increased over the next four years, placing this TA at the forefront of the identified techniques, which have not been researched much in the public service context (Guan and Tezuka 2022; Jiang et al. 2021; Li 2021; Schneider et al. 2021; Suryanarayanan et al., 2021). Here, deep learning-based models (further known as large language models) are used to ensure various language-related chatbot functionalities. For example, (Budiharto et al. 2020) propose a deep learning approach based on a recurrent neural network (RNN) encoder and a convolutional neural network (CNN) encoder with bidirectional attention flow (BiDAF) to develop a question-answering system for an intelligent humanoid robot prototype. Additionally, (Jati et al. 2020) implement bidirectional encoder representation from the transformer (BERT) multilingual cased and BERT multilingual uncased models for Indonesian health insurance question-answering system. Also, (Dimitra et al. 2022) Anastasiou et al. (2022) use ready-available BERT models for the design of a machine translation-powered chatbot for public administration.

A slight decline in the development of such techniques as *Topic modeling* and *Sentiment analysis* in recent years can be explained by the need to find solutions related to the problems of explainability and interpretation of results, especially for the specific problem domains, including the required human resources in iterative understanding, interpretation, and categorization of patterns extracted from text, going beyond automatic text analysis (Maramba et al. 2015). This fact can also explain the focus shift in 2021–2022 to *Content analysis* as one of the supporting techniques with a rigorous involvement of human experience. We further note the peak popularity of *Semantic Web and Linked Data* in 2020, wherein this TA technique accounts for 17.39% of all publications in this year. Further decline in *Semantic Web and Linked Data* research in 2022 can be explained by already reached high-level scientific achievement and the transition towards practical applications (Narayanasamy et al. 2022).

4.2 Text analytics data sources

The choice of TA techniques is largely determined by the *data sources* they are applied to. We identify eight major categories of data sources (DS1-DS8), where TA techniques support public services (see Fig. 3). *User-generated* (text or speech) data (28.8%) is the most prevalent data source, processed across Dialogue Systems like Chatbots (44.2% of TA techniques), Humanoid Robots (13.9%), and Artificial Neural Networks (9.3%); and it is the only data type utilized by all TA technique. *Social media* is the second dominant source of data (22.1%) for techniques such as Sentiment analysis (33.3% of TA techniques) and Topic modeling (24.2% of TA techniques). The third most important data source is *User complaints/requests* (20.8%), which serves as a source for Sentiment analysis (32.2% of TA) and Topic modeling (25.8% of TA). An interesting fact is that *Open-ended question survey* (7.4%) is primarily used for Sentiment analysis (23.01% of TA) and Topic modeling (23.1% of TA), but is also a source for Machine learning (36.36%) and Information extraction (18.2% of TA). The successful application of Machine learning to data from *Open-ended question surveys* could be explained by the fact that such texts are more meaningful if compared to *User-generated* content (specifically from social media). This allows for higher

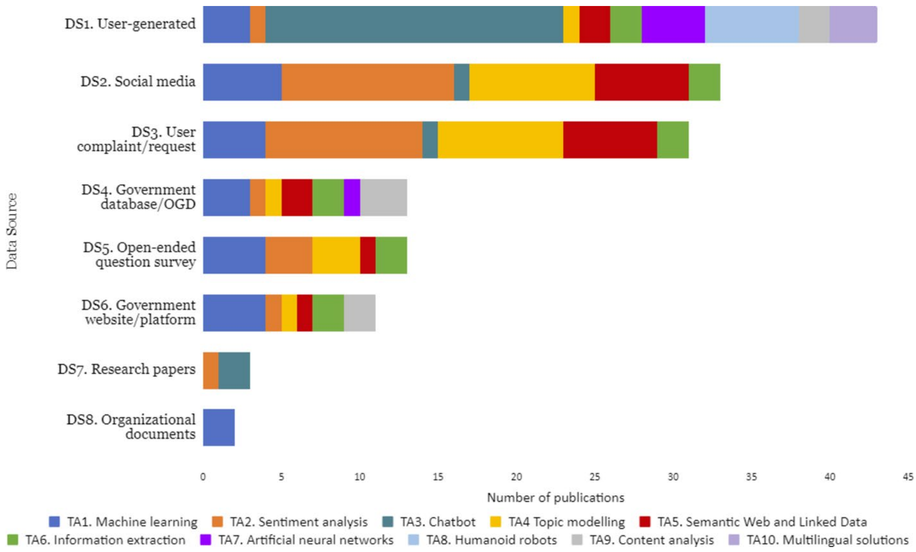

Fig. 3 Data sources and categories of TA techniques in public services

reliability and accuracy of machine learning models as well as the implementation of mixed research methods (Grimer et al. 2022). Further notable sector-specific open data sources are m*Government databases/OGD* (8.7%) and *Government websites/platforms* (7.4%). These data sources are used in Machine learning techniques (23.1% and 36.3% respectively), Content analysis (23.1% and 18.2% respectively), Information extraction (15.3% and 18.1% respectively), Semantic Web and Linked Data (15.4% and 9.1% respectively); and in Artificial neural networks (7.68%) for Government databases/OGD.

4.3 Text analytics functionalities and Public Service Areas

We extracted the main *functionalities* of TA in relation to their specific capabilities or features in the context of supporting various stakeholders in public service co-creation (RQ2) and grouped them into the eight categories F1-F8 (see Fig. 4a). The majority of the literature addresses several TA functionalities.

The most popular TA functionality in public service co-creation is A*utomatic content analysis and extraction* (32.4%), which provides valuable information and enhances both public service providers' and users' awareness of various aspects of public services and supports informed decision-making. A further popular functionality is *Patterns identification* (23.7%), which generates actionable insights to support decision-making by revealing similarities and relationships (groups, clusters, communities, trends) in documents, user behaviors, service functions, or the processes providing services. One of the top three TA functionalities is *Question-answering* (20.8%), used for the automated support of dialogue systems in natural language and automatic content generation.

Extracting meaning from user requests/complaints/opinion is a functionality (7.9%) that focuses on increasing the level of understanding of user needs to improve public services based on user complaints/requests as a data source and producing rigorous evidence for

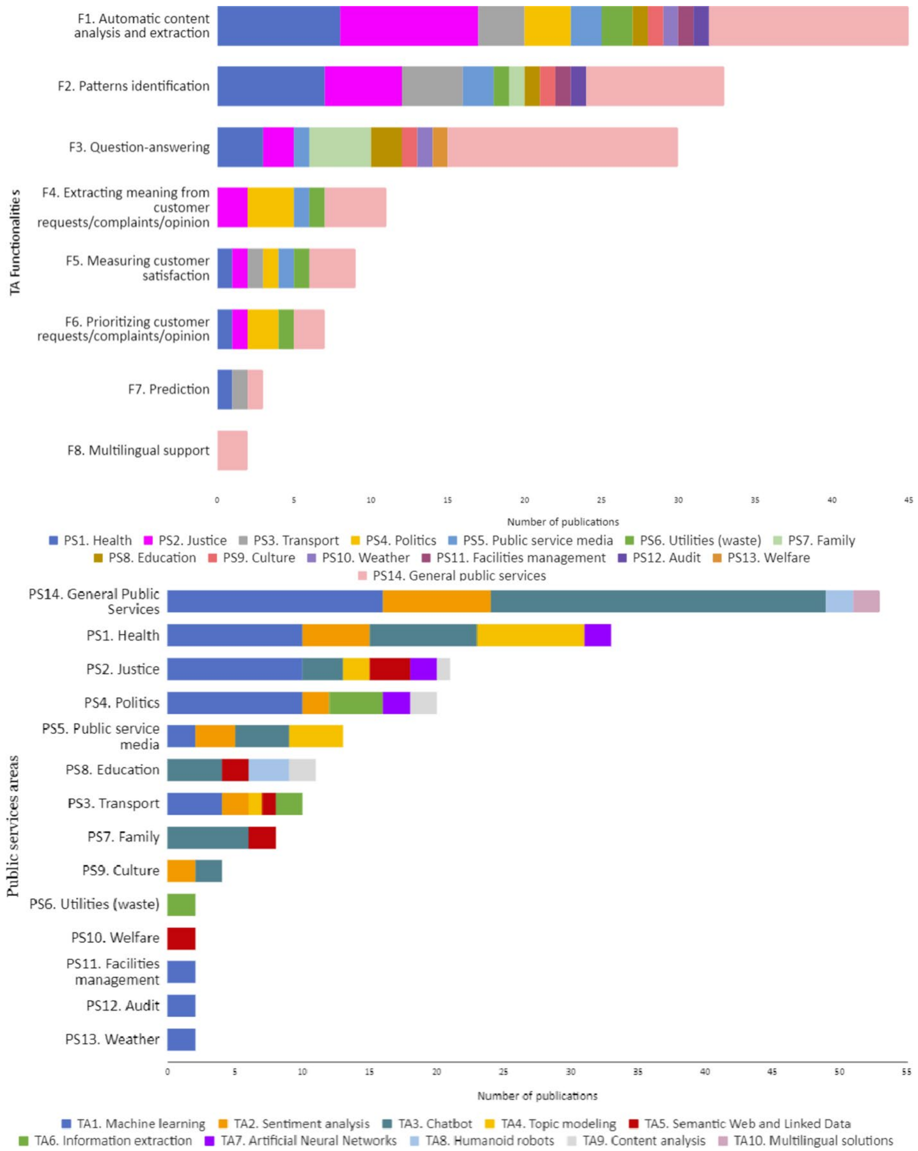

Fig. 4 a Categories of TA functionalities (RQ1) and public services areas (RQ2). b: Categories of TA techniques (RQ1) and public services areas (RQ2)

policy making and monitoring. *Topic modeling* is often implemented in combination with *Machine learning* and *Sentiment analysis*, which in turn cover all other data sources. Other functionalities are *Measuring users satisfaction* (6.47%), i.e., performing sentiment and emotions analysis; and *Prioritizing users requests/complaints/opinions* (5.0%) for quantitative assessment of the degree of significance (criticality, urgency) of the users' problems. The *Prediction of user behavior and satisfaction* (2.1%) function is still at the development stage, so in terms of proactive public service improvement requires strict validation and evaluation.

Moreover, we matched the identified TA functionalities and 13 *public service areas* (PS1-PS13, in Fig. 3a) described by the EC (The European Commission, 2022): *Health* (15.0%), *Justice* (14.3%), *Transport* (6.4%), *Politics* (6.4%), and *Public service media* (5.0%). The *General public services* were identified in *35*% of all publications. We identify the following trends:

(1) In the public service area of *Health* and *Transport*, we note an application of techniques for *predicting* various events or states that are relevant for users, such as user satisfaction, spread of infection, and transport delays. The application of these techniques is made possible by the availability of large amounts of textual data generated in these public service areas, and the need for constant monitoring and storing of quantitative indicators, such as road and traffic conditions, medical test results and basic hospital performance indicators that provide the data to improve the quality of forecasts (Ferri et al. 2022; Jastrzębska and Homenda 2021);

(2) In the *Health* and *Justice* areas, the main TA functionalities are *Automatic content analysis and extraction* (17.7% and 20.2% of all TA functionalities, respectively) and *Patterns identification* (21.2% and 15.1% of all TA functionalities, respectively). These public service areas are characterized by the presence of a large number of up-to-date and archival documents, likely to be found on government websites, platforms, or databases. These documents are a valuable source of information for extracting insights and creating new knowledge (Zhou et al. 2022);

(3) For public services in the *Politics* area, the functionalities of *Prioritizing* (28.5% of all TAs functionalities) and *Extracting meaning from users' requests/complaints/opinio*n (27.2% of all TAs functionalities) are important. The popularity can be explained as they represent the main focus of political research (Bayrak 2022; Vasconcelos 2020);

(4) In the group of studies not specifying any public service area (*General public services*), 75.5% of the literature reviewed included the following functionalities: *Question-answering* (30.6% of all TAs functionalities), *Automatic content analysis* and extraction (26.5% of all TAs functionalities), and *Patterns identification* (18.3% of all TAs functionalities). These TA functionalities are often developed in the general public services context. Hence, it may take additional time to adapt them to a further, more specific area (Vassilakopoulou et al. 2022). At the same time, the *Question-answering* TA functionality allows us to assume that the standards for supporting the development of public sector dialogue systems deployment are becoming more mature, and mostly technical challenges need to be resolved (Stamatis et al. 2020). The *Multilingual support* functionality is present only in *General public services* (PS14), which indicates its challenging contextualization for researchers and practitioners (Dimitra et al. 2022; Van den Bogaert et al. 2022).

Regarding TA techniques and their alignment with identified *public service areas* (Fig. 4b), the following observations further enrich our previous insights:

(1) Most results for *Machine Learnin*g (27.59% of this TA technique applications across identified public service areas), *Sentiment Analysis* (36.36%), and *Chatbots* (48.08%) TA techniques remain in the experimental phase, focusing on enhancing model accuracy and performance, with limited real-world applications in specific public service areas (*General public services*);

(2) *Machine learning* is a key method for implementing TA techniques like Sentiment Analysis and Topic Modeling, particularly in the public service areas of *Health* (17.24%), *Public Social Media* (3.45%), and *Transport* (6.90%). In *Health*, *Justice*, and *Politics* public service areas, machine learning, combined with *Artificial Neural Networks* (33.33%), plays a significant role in enhancing predictive accuracy and providing deeper insights. Additionally, when combined with *Chatbots* (22.73%), it supports automating processes through question-answering systems;

(3) *Chatbots* as automated support of dialogue systems in natural language and automatic content generation, are widely employed in public service areas such as *Health* (15.38%), *Family* (11.54%), *Public Social Media* (7.69%), *Education* (7.69%), *Justice* (5.77%) and *Culture* (3.85%);

(4) *Topic Modeling* TA technique strongly supports the *Health* (53.33%) and *Public Service Media* (26.67%) sectors, offering insights into patterns, themes, and emerging trends within these fields, and helping to identify key issues, assess user satisfaction, and prioritize user needs and requirements (Kowalski et al. 2020; Lee et al. 2018; Ojo and Rizun 2021);

(5) *Content Analysis*, including methods such as discourse analysis and thematic analysis, is predominantly used in the public service areas of *Justice* (20.0%), *Politics* (40.0%), and *Education* (40.0%). This TA technique is particularly valuable for examining large volumes of both up-to-date and archival documents, enabling systematic review, and uncovering patterns, and trends in public discourse (Grace and Sinor 2021); or in assessing the narrative framing of legal proceedings, political strategies, and educational reforms (Lachana et al. 2021; Vasconcelos 2020);

(6) *Semantic Web and Linked Data* TA technique plays a pivotal role in *Justice* (30.0%), *Education* (20.0%), *Family* (20%), *Welfare* (20%), and *Transport* (10%) public service areas. These areas are predominantly represented in government databases and open government data (OGD), where linked data and semantic technologies facilitate interoperability, improve data integration, and enhance decision-making processes by connecting disparate data sources and providing a more structured, meaningful representation of information (Nikiforova et al. 2023);

(7) *Justice* is the public service area represented by the largest number of TA techniques applied: *Machine Learning*, *Chatbots*, T*opic Modeling*, *Semantic Web and Linked Data*, *Artificial Neural Networks*, and *Content Analysis*;

(8) *Multilingual solutions* are underrepresented and appear only in studies on *General public services*, focusing on enhancing communication and accessibility across language barriers. Humanoid robots, another underrepresented TA technology, are not only used in general public services but have also been introduced in *Education* to support interactive learning (Budiharto et al. 2021).

5 A research framework for text analytics in public service co-creation

In this section, we aim to answer the following three research questions RQ3: *When can TA* provide *support?* (Sect. 5.1), RQ4: *Who can be involved in the design*, *development and implementation of TA for public service co-creation?* and RQ5: *What potential public value can TA provide for public service*? (Sect. 5.2). Section 5.3. presents the research framework for Text Analytics in public service co-creation.

5.1 Co-creation phases supported by text Analytics techniques

In order to present the current situation regarding TA-related research in the public services, and its potential applications and public value it brings to the public sector co-creation, in this section we aim to build a *research framework* for TA in public service co-creation by mapping the extracted TA techniques and functionalities (see Sect. 4.1, 4.3.) to the co-creation phases and mechanisms. In response to the research gap identified– a limited number of studies that explore TA applications in supporting the co-creation of public services– the mapping was carried out by identifying the *theoretical potential of TA applications* to each phase of public service co-creation.

As the study results show (see Fig. 5), most of the research focuses on the potential application of TA to support the Co-design phase (71.03%). The *Co-evaluation* phase was mentioned in 24.30% of the literature, whilst only 4.67% considered the *Co-delivery* phase. It is important to note that some of the papers address two phases of co-creation and multiple mechanisms. Whereas the majority of the studies (73%) are related to only one co-creation phase, there is a trend (27%) showing the use of TA techniques in two phases. Accordingly, 20.27% of the analysed papers cover *Co-design* and *Co-evaluation* phases. Only a few studies (6.76%) consider the *Co-delivery* and *Co-design* phases. This distribution may be due to (i) the research character of the papers, i.e., the suggested solutions are likely to be used during the design and evaluation phase, as well as (ii) the analytic nature of TA.

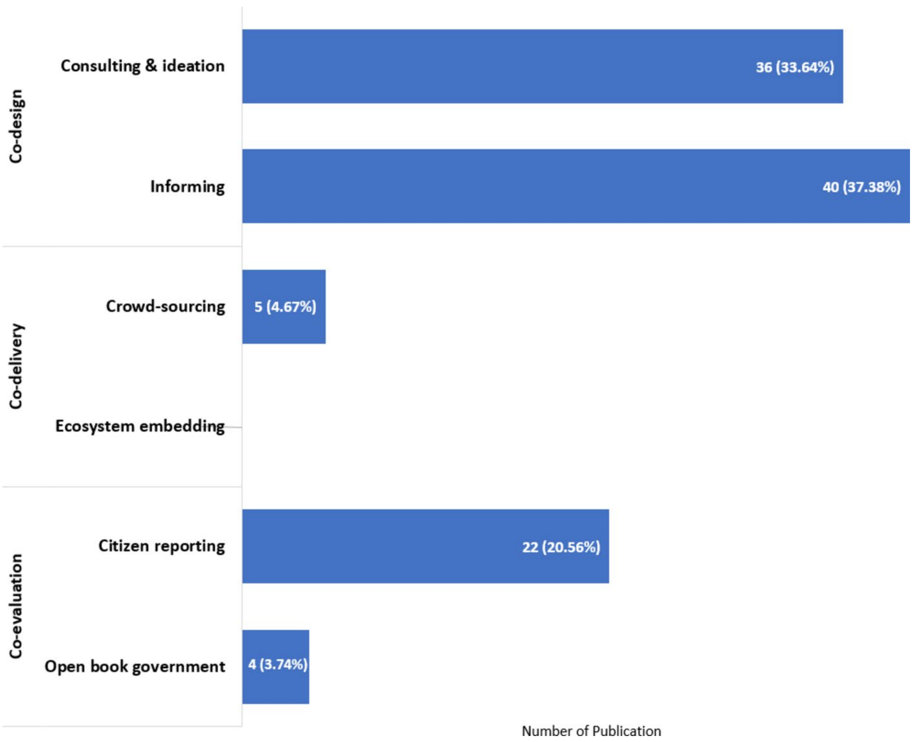

Fig. 5 Co-creation phases and mechanisms (RQ3) supported by TA techniques (RQ1)

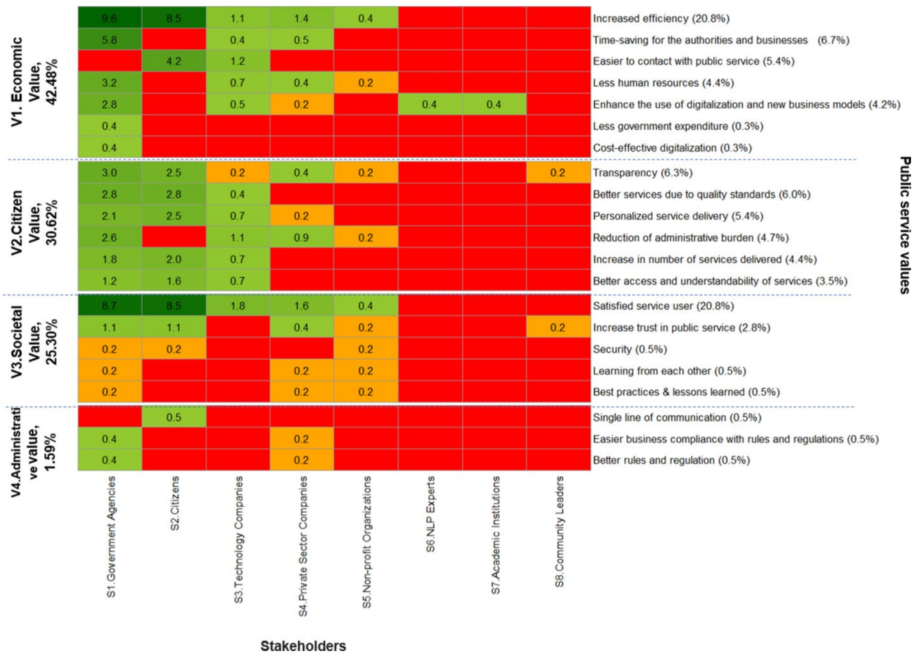

Fig. 6 Potential TA-based public service values (RQ5) mapped to stakeholder groups (RQ4)

The most popular co-creation mechanisms are, as expected, *Informing* (37.38%) and *Consulting & ideation* (33.64%) during the *Co-design* phase. In the Co-evaluation phase, the *Citizen reporting* mechanism is the most prevalent (20.56%). In the Co-delivery phase, the *Crowdsourcing* mechanism is popular (4.67%). The lack of research on the application of TA technologies to support the *Ecosystem embedding* mechanism during the *Co-delivery* phase may be explained by the complexity of the practical implementation of this mechanism due to the absence of a well-defined theoretical and legal basis and a lack of government responsibility for the implementation results of such activities (Linders 2012).

Appendix A.7 contains the summary of the results of TA technique categories extracted and assigned to each of the co-creation phases and mechanisms.

5.1.1 Co-design

The Co-design phase provides an important basis for the concept and design of the service to be developed (Rodriguez Müller et al. 2021). Based on the concept, we have adopted the two main mechanisms of the *Co-design* phase: *Consulting & ideatio*n and *Informing* (Linders 2012).

According to the results of our analysis, a *Chatbot* shows a high potential to support the Co-design phase, in particular, the *Consulting & ideation* mechanism enabling people to support two-way communication between stakeholders and public administration in the context of service improvement, making it easier to provide questions and revive answers in text or voice form by eliminating time and location constraints and laying an important basis for the public service personalization, e.g., (Damij and Bhattacharya 2022; Dimitra et al. 2022; Gerontas et al. 2022; Heo and Lee 2019; van Noordt and Misuraca 2019; Zhu et al. 2022). State-of-the-art chatbot technology also allows a convenient, time-independent notification of citizens regarding service updates, and events. *Humanoid robots* can be considered a more social, however not frequently used, physical alternative to chatbots. Addressing the limitations of intelligent interaction, (Budiharto et al. 2020) propose a humanoid robot with the self-learning capability for accepting and giving responses to be used extensively in public services. *Artificial neural networks* have yet to find wide application in public service co-creation due to limitations around trust, transparency, and ethical concerns. However, several potential cases were identified to support *Consulting & Ideation* mechanisms, aiming to facilitate citizen-to-government and citizen-to-citizen interactions, such as support for multilingual translation-powered chatbots (Andreas et al. 2019; Dimitra et al. 2022).

Further popular TA techniques include the application of *Semantic Web and Linked Data* in the *Co-design* phase, particularly during the *Consultation & Ideation mechanisms* and *Informing*. These TA techniques provide a structured framework that enables two-way communication between stakeholders and public administration, facilitating the integration and reuse of information in a semantically interoperable way (Amara et al. 2022). This framework allows stakeholders to share questions, suggestions, or requests regarding public services via digital platforms, social media, or public service delivery systems equipped with question-answering systems, such as chatbots or virtual assistants. Building on this, research has focused on enhancing the CPSV-AP, a standardized European public service data model, to improve the creation of public service catalogues and enable semantic interoperability (Antoniadis and Tambouris 2021; Stamatis et al. 2020). The development of such vocabularies and ontologies enables various expert systems to support informed decision-making (*Co-design* phase, Informing mechanism), such as automated legal expert systems that provide cross-country legal information within the EU based on existing ontologies (Avgerinos Loutsaris et al. 2021).

Information extraction and *Multilingual solutions* are the least used TA techniques. They can be used during the *Co-design* phase as *Consulting & ideation* mechanisms, and rely on interactivity, used, for example, as a question-answering system when consulting with health insurance (Jati et al. 2020), supporting citizens to fill out online forms (Magnini et al. 2000), or enabling users from all EU member states to access and use public services in their own language (Van den Bogaert et al. 2022).

Machine learning, including text classification, clustering, and summarizing, are the most developed TA techniques; they support the *Informing* mechanism of the *Co-design* phase. These TA techniques are efficient for processing large amounts of text, extracting relevant information, and preparing for further transmission, i.e., enabling informing citizens with a targeted message rather than overwhelming them with large amounts of content. Several researchers are evaluating the status and progress of smart city development projects (Hu and Zheng 2021), assisting policy-makers in discovering associations between existing policies, proposed policies, and citizens' opinions expressed on electronic public forums (Rao and Dey 2011), and predicting irregularities in public sector records concerning reimbursement policies (Santos et al. 2015).

In this respect, *Topic modeling* appears to be the second most potentially useful technique that could be used during the *Co-design* phase as an *Informing* mechanism. Topic modeling is applied to extract key aspects discussed by service users or in official published reports. The topics identified can be prioritized by the extent to which they are discussed (Ferri et al. 2022). In combination with *Sentiment analysis*, these topics can be ranked based on the degree of emotion that a certain topic evokes and enable the government to deliver highly personalized information (Linders 2012; Miranda and Bringula 2021; Muktafin and Kusrini 2021). The results of the analysis can be shared with the relevant authorities and citizens in order to increase user satisfaction, augment human decision-making, and enhance the speed and quality of public services (Berryhill and Clogher 2019; Peet et al. 2022).

5.1.2 Co-delivery

The *Co-delivery* phase presupposes the involvement of the trained stakeholders (for example, public servants, and peer groups) in providing public services and is "concurrent to the service" (Linders 2012; Nabatchi et al. 2017). Two main mechanisms can be used to describe the *Co-delivery* phase: *Crowdsourcing* and *Ecosystem embedding.* Our review confirms what other authors have noted: a poor understanding of the nature and mechanisms of service co-delivery processes (Bovaird and Loeffler 2012; Rodriguez Müller et al. 2021).

A few potential TA techniques for supporting the *Crowdsourcing* mechanism during the Co-delivery phase have been identified, although most studies focus primarily on the *Co-design* phase. For example, *Chatbot* and *Machine learning* techniques led to the creation of CitiCafe, a Twitter-based conversation platform (Dumrewal et al. 2018) that automates the citizen consultation process. This platform allows citizens to submit queries and interact with a question-and-answer system, receiving text explanations that remain visible to all users of the platform. This functionality is associated with the *Co-design* phase, *Consultation and ideation* mechanism. In addition, the platform supports a citizen-led consultation mechanism, allowing users to search for answers to similar complaints/queries, view information on civil issues in various areas, and receive direct advice in the form of comments and responses from citizens with similar problems, experiences and solutions. In the proposed research model (Table 1), this corresponds to the basic principles of *Co-delivery* phase, *Crowdsourcing* mechanism, and has great potential for further development and use.

Machine learning and *Semantic Web and Linked Data* are used in legal public services for generating reports based on the processing of legal data (*Co-design* phase, *Informing* mechanism). However, in the context of the *Co-delivery* phase, TA can support the process of finding semantic relationships within court transcripts to support judges' decision-making (Ratnayaka et al. 2019) and to retrieve information from legal online repositories based on semantic similarity (Sugathadasa et al. 2019) (*Crowdsourcing* mechanism). In the process of supporting the *Co-delivery Crowdsourcing* mechanism, TA methods also allow the use of the judges' knowledge for automating the provision of legal public services, where judges play the role of experts both for (i) developing rules governing the selection of the most appropriate court decisions used in machine learning model and (ii) evaluating the results of the semantic similarity degree between legal documents. The understanding of using TA as a tool to enhance public service co-delivery in this context requires further development.

5.1.3 Co-evaluation

The Co-evaluation phase allows the assessment and monitoring of the public service after it has been delivered to learn from it, revise or improve the service quality (Nabatchi et al. 2017; Rodriguez Müller et al. 2021; Sicilia et al. 2016). Two main mechanisms are adopted in this study to describe the *Co-evaluation* phase: *Citizen reporting* and *Open book government.*

Sentiment analysis is the most developed TA technique for supporting the *Citizen reporting* mechanism during the *Co-evaluation* phase. In this phase, *Sentiment analysis* is employed for both the qualitative evaluation of citizens' feedback and the quantitative measurement of the positivity or negativity of their attitudes towards specific services and related issues; and enables the assessment of citizen satisfaction (using sentiment scores) (Ferri et al. 2022; Muliawaty et al. 2019). *Topic modeling* and *Machine learning* appear to be further two TA techniques that can potentially be used to support the *Citizen reporting* mechanism. The combined use of Sentiment analysis, Topic modeling, and Machine learning in public service co-evaluation offers several advantages: (i) enable a thorough *prioritization* of public service-related issues based on topic proportions and sentiment score indicators, whether separately or together (Das et al. 2020; Lee et al. 2018); (ii) the tracking of the *changes* in topic proportions and topic context related to the citizens' experiences over time (Ojo and Rizun 2020); and (iii) the detection of the *demographic differences* in topic proportions and topic valence (sentiment scores); and (iv) estimating the power (measured by Gini Importance Index) of topics to *predict* public service ratings, using Random forest model where rating was chosen as a dependent variable and Topics proportion– as predictor variables (Ojo and Rizun 2021). The insights gained from these TA techniques can be shared with relevant authorities and citizens, helping to improve citizen well-being and enhance the sustainability of public services. The *Artificial neural networks* and *Information extraction* for *Citizen reporting* mechanisms are mostly used to complement other TA techniques to: (i) develop a more robust and meaningful solution and increase citizen-centric public service quality (Reddick et al. 2017), for example, by analyzing citizen-government communication for user profiling and satisfaction inference (Flores et al. 2022), (ii) determine the factors affecting the users' polarity (Kim and Hong 2020), and (iii) identify urban events and public service problems (Gonzalez et al. 2021).

The *Open book government* mechanism during the Co-evaluation phase was identified in a few studies and represents a special form of the *informing* process focusing on proactive dissemination of open access datasets and allowing individuals and civil society organizations to view and *re-use* vast amounts of government data for other purposes. These open datasets can be useful to increase citizens' understanding of issues of interest and to provide and make informed personal decisions. In the identified studies, TA techniques support the *Open book government* mechanism and are demonstrated in applications such as (i) the automatic generation of ocean weather public reports (*Content analysis* and *Information extraction*) (Bai et al. 2019), (ii) the forecasting of the outcomes of future elections (*Machine learning* and *Sentiment analysis*) (Zainol et al. 2021), and (iii) the automated identification of national implementations of European directives (*Artificial neural networks* and *Machine learning*) (Nanda et al. 2019). Furthermore, chatbots utilizing *Semantic Web and Linked Data* technologies have been launched to provide easy access and intelligent search functionalities, enabling users to explore and interact with open government data (Cantador et al. 2021). These tools not only enhance transparency but also empower stakeholders to gain deeper insights into public administration, make informed personal decisions, and hold public institutions accountable.

5.2 Potential public service values and stakeholders

As mentioned above, most TA solutions have been introduced in the general public service context, allowing for applications that can be used across various services (cross-service). In this respect, the following research questions were posed. RQ4: *Who can be involved in the design, development and implementation of TA for public service co-creation?* and RQ5: *What potential public value can TA provide for public service*?

The Fig. 6 presents the distribution (in %) of 21 public values, grouped into four categories, mentioned in the analyzed literature as either expected or achieved and potentially associated with TA support of public service co-creation. As the results show, *economic values* (42.48%) of TA for public service most frequently occurred in the studies. The top three *economic* values that can be obtained by applying TA techniques are increased efficiency (20.88%), time-saving for the authorities and businesses (6.73%), and more accessible public services (5.49%). The use of sentiment analysis (Muktafin and Kusrini 2021), text mining algorithms (Gonzalez et al. 2021), and chatbot services that provide immediate information to citizens 24/7 (Stamatis et al. 2020) increase the efficiency of public service and contribute to cost savings. TA techniques, including humanoid robots (Budiharto et al. 2020), machine translation (Dimitra et al. 2022), and chatbot services help to resolve common and straightforward requests and contribute to a more pleasant and efficient provision of public service.

The second group is represented by *citizen* values (30.62%), where transparency (6.37%), higher quality public services (6.02%), and personalized service delivery (5.49%) represent the most important dimensions. TA techniques are known for their capability of processing and extracting meaning from large amounts of text from multiple sources. The automated identification of national implementations of European directives based on a large legal text corpus (Nanda et al. 2019) can increase transparency and reveal how far the directives are implemented at a national level. Service automation solutions supported by chatbots (Henman 2020) and assistance in filling the documents (Antoniadis and Tambouris 2021) reduce administrative efforts and contribute to better quality service.

The third group are *societal* values (25.30%), where the *satisfied service user* (20.88%) is the most important dimension. As the goal and outcome of any public service should be better or more user satisfaction, then TA techniques, such as chatbots, sentiment analysis, and machine learning-based TA, should aim to achieve this goal too.

The fourth and least represented group includes *administrative* values (1.59%). These are more “hands-on” and practical values, and also the ones where the potential of using TA techniques is hardest to derive. For example, designing a chatbot service or investigating possible options of chatbot applications for public service delivery (Makasi et al. 2022) implies the revision, adaptation, and improvement of existing administrative rules and regulations.

Moreover, five main *stakeholder groups* that can be involved in the design, development, and implementation of TA for public service co-creation were identified in our study. Figure 6 presents the results of mapping the discussed TA-based *public service values* to specific public service stakeholder groups. The results proved that the main stakeholders are *government agencies* (S1) and *citizens* (S2), and the most important public service values are (i) increased efficiency and (ii) service user satisfaction. For example, analysing citizens’ feedback on Social Media allows them to proactively improve public services, and increase their efficiency and user satisfaction (Kowalski et al. 2020). An essential, though not primary, stakeholder identified in the study is *technology companies* (S3) that provide TA solutions to government agencies, including those developing advanced expert systems (Lachana et al. 2021) or humanoid robots (Andreas et al. 2019). Collaborating with technology companies can be critical for the successful implementation of the TA solution in the co-creation of public services. Private sector companies (S4) may provide support for public services through partnerships, sponsorships, and direct service delivery through service outsourcing. In the collaborations with these stakeholders, increased efficiency and satisfied service users are the main public service values addressed. Other stakeholders are (i) *Non-profit organizations* (S5); (ii) *NLP experts* (S6); (iii*) Academic institutions* (S7) conducting research and providing expertise to inform the development of NLP solutions for public services; and (iv) *Community leaders* (S8) participating in co-creation by providing local perspectives and representing the needs of their communities.

5.3 Research framework

The research framework for the application of TA techniques to support research on public service co-creation is presented in Fig. 7. The primary *objectives* of this research framework are (1) to *systematically organize* the knowledge presented in existing literature on the potential application of TA in public services; (2) to emphasize the *powerful role* of TA in effectively supporting public services co-creation; and (3) to increase *awareness* among

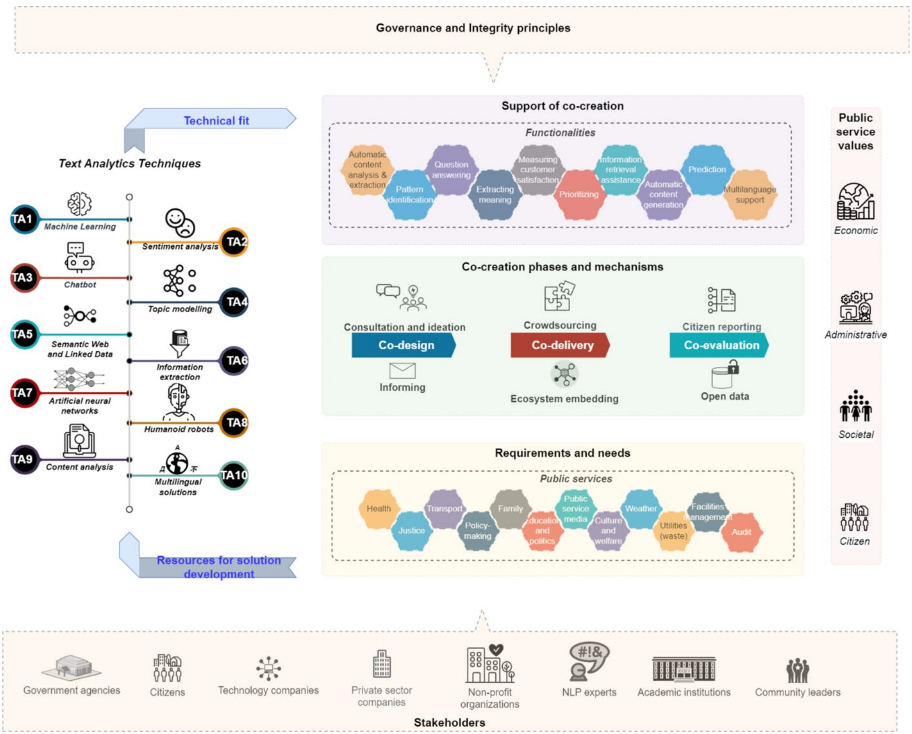

Fig. 7 The research framework for TA techniques to support public service co-creation

public sector organizations and various stakeholders regarding the potential of TA in public services value creation. The developed framework reflects the main purpose of co-creation as an activity that allows public administrations to understand stakeholders' demands and an important mechanism where users can contribute their knowledge and skills (Torfing et al. 2016).

Our research framework incorporates ten TA *techniques* (Sect. 4.1) and, based on their *technical fit* through ten identified TA *functionalities* (Sect. 4.2), outlines the potential *support* these techniques can offer across the various phases of public service co-creation. The *co-design* phase provides an essential frame for the design of the service and the engagement of the relevant *stakeholders*, such as citizens, technology or private sector companies (see Sect. 5.2), through the mechanisms of consultation, ideation, or providing information. The *co-delivery* phase, including mechanisms of crowdsourcing and ecosystem embedding, includes the *stakeholders* providing their knowledge during the delivery of a service. The *co-evaluation* phase includes s*takeholders'* (citizens) reporting and open data mechanisms that enable them to assess the service after it has been developed and delivered.

The proposed research framework also reflects the contribution co-creation, supported by TA, makes to achieving the four *public values* (see Sect. 5.2). We suggest that TA techniques can facilitate co-creation, helping to realize economic, administrative, societal, and citizen *values.* Different *public service types*, like health, justice, and transport (see Sect. 4.3), are characterized by their own specific *requirements and needs*, so have to be carefully considered during each co-creation phase. Public services provide the *resources*, such as experts, and data, necessary for the development of the *TA-based* solution. The research framework provides a holistic overview of the potential of TA techniques integration in public service co-creation and can serve as a valuable tool for conducting in-depth investigations, leveraging existing contributions, formulating government strategies, and conducting thorough thematic searches.

5.4 Challenges of using text analytics in public service co-creation

In this section, we discuss the challenges identified in applying TA to the co-creation of public services and highlight the importance of incorporating *Governance & Integrity Principles* into our research framework (Sousa et al. 2019). These principles will help establish regulatory mechanisms that address potential risks, ensuring TA applications align with ethical standards and support a smooth and sustainable transition to effective TA-enabled public service co-creation.

We found that one-third of the analyzed papers focus on developing TA techniques for "general" public service purposes, with broad, experimental goals rather than targeting specific real-world applications (see Fig. 8). This trend helps explain why most identified challenges are *technical*, comprising data-related issues, technical execution, and interpretability (65.52%), and *Ethical and legitimacy*-related challenges are discussed significantly less frequently (34.48%). Additionally, challenges related to organizational and managerial aspects– such as procedural issues, institutional capacity, and levels of organizational learning necessary for implementing TA-based solutions in public administration (Mariani et al. 2023)– did not receive enough attention in the literature.

One of the most frequently mentioned *Technical* challenges in the analyzed studies is *data-related* (28.74%), especially apparent when applying techniques like *Machine learn-*

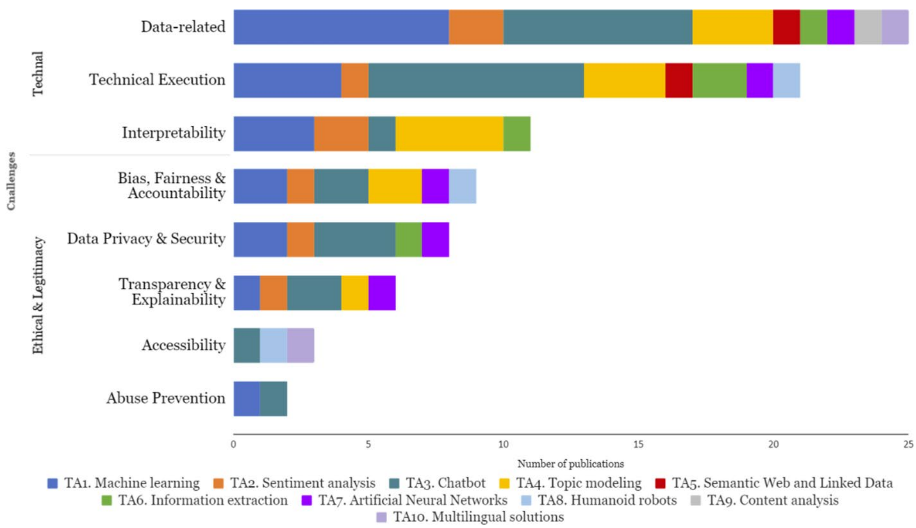

Fig. 8 Challenges of using TA techniques to support public service co-creation

ing and *Chatbots*. This includes such issues as data unavailability (Hu and Zheng 2021) and scarcity (Moreira Valle et al. 2022); the need for intensive data cleaning and processing (Lee et al. 2021); diverse and heterogeneous data sources (Ittoo et al. 2016); inconsistencies and high annotation costs (Moreira Valle et al. 2022); and the lack of gold standards or annotated data (Nirala et al. 2022). Another common set of challenges pertains to the *technical execution* of TA-based solutions (24.14%), with 38.09% specifically related to *Chatbots* functionality, particularly issues like response accuracy (Henman 2020; Jones and Jones 2019; Stamatis et al. 2020); seamless integration of TA tools with existing systems (Elbattah et al. 2021); handling large data volumes (Agarwal and Sureka 2017); ensuring that technical features and capabilities align with the service's complexity level (Jones and Jones 2019; Makasi et al. 2022); developing and deploying semantics-driven services (Salem et al. 2018); and architectural scalability (Baltaxe et al. 2022). The complexity of *Machine learning*-based models, combined with the lack of explainability of their algorithms and outputs, often creates challenges in understanding of results, leading to a trade-off between accuracy and *interpretability* (Peet et al. 2022). In this context, TA techniques like *Topic Modeling* and *Sentiment Analysis* face significant challenges related to low explainability and difficulty in result interpretation (12.64%) and require careful consideration of *context-specific* problem domains (Ojo and Rizun 2021). The effective application highly depends on rigorous regulation of expert knowledge input, and need for strict validation of the results of topic labeling (Maramba et al. 2015; Ojo and Rizun 2021), and the interpretation and categorization of patterns extracted, going beyond what fully automated analysis can achieve.

An essential, stand-alone set of challenges involves the *Ethical & Legitimacy* challenges (34.48%) of implementing TA techniques. Among these, *biases* are frequently highlighted as a primary challenge (10.34%), particularly as TA algorithms, when trained on skewed datasets, can unintentionally perpetuate and amplify existing societal inequalities. This can lead to discriminatory outcomes and *unfairness*, disproportionately impacting certain groups and affecting the equitable design of public services. This issue also referred to as an "administrative justice challenge" (Henman 2020), relates directly to the "responsibility challenge," where *accountability* for AI-driven decisions in co-created services becomes complex (Jarke 2021; Ruijer and Meijer 2020). Biases in TA applications, especially during phases of citizen feedback and consultation, may distort the genuine representation of public needs and hinder equitable input into service development. To support fair co-creation, public administrations can mitigate these risks by diversifying data sources, regularly auditing algorithms, and implementing bias mitigation techniques (Zuiderwijk et al. 2021). Integrating "human-in-the-loop" processes allows experts to oversee and adjust model outputs, helping to prevent biases from impacting critical decisions. Additionally, *automation bias*– where there is a tendency to rely excessively on AI recommendations– can lead participants in co-creation to overvalue machine-generated outputs and emphasizes the need for balanced human oversight in decision-making (Goddard et al. 2012; Ruschemeier and Hondrich 2024). Such oversight helps maintain legally secure TA techniques use, ensuring safety, accountability, and human autonomy, as underscored in the European Commission's AI guidelines[2].

In public service co-creation contexts, TA applications often manage sensitive data– such as personal conversations, feedback, or issue reporting– shared by users throughout all stages of the co-creation process (Rafail and Efthimios 2020). This introduces *data privacy* and *data security* risks (9.20%) that necessitate rigorous data protection and transparent communication. To mitigate these risks, the EU General Data Protection Regulation (GDPR[3]) standard mandates practices like data minimization, anonymization, secure storage, and transparent communication regarding data collection and usage. For example, all personal information exchanged with citizens or public administration agencies, including passwords, should be encrypted through crypto-protocols and anonymization (Toots et al. 2017); users should receive clear privacy notices and have the option to consent or withdraw consent at any time (Androutsopoulou et al. 2019; Zuiderwijk et al. 2021). Adopting a Privacy-by-Design approach (GDPR 1970) is essential, embedding privacy protocols into the system architecture from the outset through methods like pseudonymization and regular privacy updates to meet evolving standards (Romanou, 2018). These safeguards will enable the positive interchange nature of diverse information types crucial for effective co-creation.

A significant challenge in TA applications is ensuring *transparency* and *explainability* (6.90%), especially within public sector co-creation processes. To build trust, these systems must provide clear, accessible explanations of how insights and decisions are generated, allowing citizens to understand the basis for feedback on their proposals or comments. The integration of practical Explainable AI (XAI) techniques makes AI decisions more comprehensible to users. Some effective methods include visual explanations (for example, decision trees or attention maps can illustrate which factors influenced a recommendation or feedback (Kim and Hong 2020; Selvaraju et al. 2017); model documentation (Barclay et al. 2021), including details on data sources, potential biases, and guidelines on when the model operates autonomously versus supporting human decision-making; human-in-the-loop reviews (Tsiakas and Murray-Rust 2022), combining automated processes with human oversight, where AI outcomes are reviewed and potentially adjusted by human moderators. This solution should emphasize three key aspects: making AI operations understandable,

[2] *AI Act*.

[3] https://gdpr.eu/.

clearly communicating where and how AI is used, and clarifying the distinction between AI-driven decisions and those it only supports (Balasubramaniam et al. 2023). Traceability further ensures decisions can be traced back to their sources, balancing transparency, privacy, and auditability. Together, these practices aim to enhance fairness, accountability, and public trust in TA-driven support for public sector co-creation (van Noordt et al. 2023).

Although *accessibility* issues are less frequently mentioned (4.60%), they play a crucial role in fostering inclusivity, ensuring broader public access, and enhancing understanding. In the analysed literature, these include precise language identification (Dimitra et al. 2022), building meaningful user profiles to correctly infer user satisfaction (Flores et al. 2022); correct interpretation of user intentions by chatbots (Chen, 2020) and achieving accuracy and consistency in machine translation (Magnini et al. 2000). Such issues are particularly relevant to *Chatbots*, *Humanoid Robots*, and *Multilingual solutions*.

The distinct category of challenges is *abuse prevention* (3.45%). Integrating abuse prevention into two-way communication mechanisms is essential for preserving the integrity of public sector co-creation processes and maintaining productive public discourse. However, this challenge receives comparatively less focus than others due to its complexity and the specific expertise required to address nuanced abuse patterns within diverse, interactive environments. Advanced TA techniques, such as identifying patterns of discriminatory language (Ackerman et al. 2016) and detecting misleading information (Gaozhao 2021), combined with fact-checking systems (K. Das et al. 2023a, b; Sethi et al. 2024) and neural network-based models for harmful content moderation (Gongane et al. 2022; Naz and Illahi 2023), can help flag discriminatory content for human review. However, even state-of-the-art TA technologies cannot fully replicate human judgment and remain insufficient for fully automating abuse prevention. Human-centered approaches that augment human capabilities are essential, utilizing methods like active learning (Zhang et al. 2021), interactive machine learning (Raees et al. 2024), and decision support systems where humans make the final decision based on model outcomes and explanations (Zanzotto 2019). Furthermore, clear guidelines and regulation rules are needed for human moderators, including timeframes for removing and blocking 'unlawful' messages and procedures for sharing message originator information and verifying identities with authorized agencies.

Given the numerous challenges in TA-supported co-creation for public services stemming both– from the complexity of co-creation mechanisms and the nascent state of scientific and practical interest in this area– it is particularly important that all phases of TA application adhere to *policies* and *ethical standards.* Compliance with frameworks such as the European Commission's Ethics by Design Principles (European Commission 2021), the Ethics Guidelines for Trustworthy AI (European Commission 2019), the General Data Protection Regulation[4], the Data Governance Framework, and the AI Act[5] are crucial for ensuring responsible and sustainable integration of TA in public services. Policymakers, public administration agencies, and stakeholders should collaborate to establish clear guidelines for developing and deploying TA tools in public service co-creation, emphasizing adherence to regulatory frameworks and ethical principles, including respect for human agency; privacy &data governance; fairness; individual, social, & environmental well-being; transparency; and accountability & oversight. Therefore, our research framework integrates *Governance*

[4] https://gdpr.eu/.

[5] *AI Act*.

and Integrity Principles across all layers of TA applications in public service co-creation for addressing the complex challenges identified and extending beyond those identified in our study, ensuring TA tools operate ethically, transparently, and effectively.

6 Conclusion

This study seeks to contribute to the knowledge and perspectives in the context of potential applications of TA to support the co-creation of public services. To achieve the *first research objective* (O1), we conducted a systematic literature review, and the results were structured and presented accordingly. The systematic literature review is based on the analysis of 75 publications, addressing characteristics such as year of publication, country, research methods, and extracted information on the TA techniques applied in public services, functionalities related to specific capabilities and service features, public service areas, co-creation phases and mechanisms, stakeholders, and expected values.

In line with the *second research objective* (O2), we developed a research framework for TA techniques that support public service co-creation. In response to the research gap identified– the limited number of studies that explore TA applications in supporting the co-creation of public services– mapping TA techniques, functionalities, and values extracted from the literature onto the main co-creation phases and mechanisms illustrates the *potential* TA applications may have in public service co-creation.

Regarding the public service co-creation cycle, we found that 71.70% of the potential applications of TA support relate to the *co-design* phase. This can be explained by both (i) the prevalence (71.03%) in the existing literature of typically analytical and well-developed TA functionalities, such as content analysis and pattern identification, which are actively employed to understand users' needs, requirements, and expectations, thereby driving public service improvement and co-design; and (ii) the growing popularity of question-answering systems, which enhance public administration responsiveness mostly at government-citizen consultations and ideation level (Cortés-Cediel et al. 2023; Rodriguez Müller et al. 2021). The potential for TA applications to support the *co-evaluation* phase is significantly lower (24.30%). The results show that key TA functionalities during this co-creation stage– such as measuring users' satisfaction, prioritizing users' requests/complaints/opinions, and predicting user behavior and satisfaction– account for only about 21.49% of the total TA support. These TA functionalities predominantly depend on techniques like Sentiment Analysis and Topic Modeling, which still present challenges, particularly regarding the complexity of explainability, especially within specific problem domains, and the need to establish rigorous guidelines for human intervention to iteratively interpret, understand, and categorize patterns extracted from text, exceeding the capabilities of automated text analysis (Maramba et al. 2015; Ojo et al. 2024). Artificial Neural Networks, which are often employed for prioritization and prediction functionalities, are to be found during experimental stages rather than practical implementation. Proactive information dissemination, such as open book government, is an approach where the organisation allows internal and/or external stakeholders to view financial records, expenses, sources of profit, and other detailed operating information (Davis 1997). Whilst this may be of significant value for public administrations, public sector organisations have not embraced it, so this TA mechanism as yet does not support the co-evaluation phase (3.74%). Potential TA applications during support development are available to a very limited extent during t*he co-delivery* phase (4.67%). This can be explained by the absence of a well-defined theoretical and legal basis and a lack of government responsibility for the implementation results of such activities (Linders 2012).

This study proposes and defines the public value of TA. The *economic* values are the most important values that can be generated by applying TA techniques, such as increased efficiency, time-saving, and more accessible public services (Jacobs et al. 2018; Rodriguez Müller et al. 2021). This value, in particular, can support the further implementation of co-creation and the use of TA to enhance co-creation efforts in public sector organizations (PSOs).

The research framework not only enables interested *academics* to find promising *avenues for further research* but also represents an important *theoretical contribution* to the structuring of TA-enabled public service co-creation processes. The proposed framework serves as a basis and highlights the need for the development of *further guidelines*, *methods*, *and standards* for responsible and explainable AI and the interests of various stakeholder groups when using public value to motivate and involve them in a co-creation process. Similarly, for *practitioners*, the proposed framework promotes the integration of TA into all phases of the public services co-creation process. The framework may be used as a *roadmap* for building a strategy for user-centric public service design from the perspective of policy-makers and e-government managers, therefore motivating further practice-oriented case studies, improving the involvement of stakeholders, and understanding end-users needs.

Addressing the *third research objective* (O3), we identified *five* fundamental *research gaps* illuminated from the developed framework and motivated academics and practitioners to new research avenues. The *first* research gap pertains to the lack of research that specifically focuses on *theory-building*, and the development of frameworks, strategies, and research agendas to support public service co-creation using TA. Co-creation is an important paradigm in which a common body of theoretical statements has been developed and applied to a diverse set of empirical contexts. There are three main theoretical perspectives: service science, innovation and technology management, and marketing and consumer research (Galvagno and Dalli 2014). The call for a comprehensive taxonomic framework to contextualize research efforts in the area of co-creation is not new: developing models, studying the impacts of specific factors on the outcomes, and developing and using theories and instruments from various disciplines will contribute to a cumulative body of knowledge of co-creation (Zwass 2010).

The *second* research gap involves the absence of research addressing the *practical implications of TA*, such as methods, algorithms, and applications that can effectively *contribute* to and *enhance* the co-creation of public services. Public administration must be able to make informed and strategic decisions as to which public services are most suitable to be improved through co-creation (Vrbek and Jukić 2024); at the same time, co-creation should improve the functioning of the public sector through a better understanding of social challenges and attract new resources to meet such needs (Van Gestel et al. 2023)

The *third* research gap highlights the *disproportional* and *fragmented* development of co-creation phases within the public service cycle. In terms of disproportionality, it is necessary to understand the reasons behind the strong emphasis on exploring the potential of TA in the co-design phase and the practical lack of TA solutions that align with the criteria for co-delivery support (Rodriguez Müller et al. 2021). These factors likely point not to the inherent potential of TA technologies themselves, but rather to a lack of awareness among researchers and practitioners, as well as insufficient understanding of the concepts and tools required for implementing the co-delivery phase, even in analogue form (Linders 2012). Additionally, there is a lack of clarity regarding the underdeveloped state of Open Book Government mechanisms in the co-evaluation phase in the public services context, despite significant advancements in Open Government Data (OGD) aimed at promoting transparency, citizen participation and trust, and economic and service benefits of open data at the public sector organisations level (Ruijer and Meijer 2020). These issues warrant deeper investigation. As for the fragmented nature of the public service co-creation cycle (with 73% of studies addressing only one phase of co-creation, and 27% of studies indicating the use of TA techniques in two phases), empirical research could examine whether and how TA support for public service co-creation across the entire service cycle fosters greater public value creation. Addressing this gap will require comparative studies of initiatives implemented at various co-creation stages (Rodriguez Müller et al. 2021).

The *fourth* research gap identified in our study addresses the limitations of TA techniques, which, while effective in supporting sector services, remain largely unexplored in the context of public service co-creation. To bridge this gap, extensive literature reviews combined with expert assessments (Lnenicka et al. 2024) are recommended to evaluate the applicability of these TA techniques for specific public service co-creation processes. This research should consider the distinct characteristics and needs of public service environments, along with stakeholder insights, to ensure that TA techniques are adapted in a way that is both relevant and impactful.

The *fifth* research gap identified is the co-creation of *sustainable* public services, the sustainability of co-creation processes and the individual phases, the implementation of TA across all co-creation phases, and the need to consider the ethical use of TA. The long-term, iterative nature of sustainability has implications for public services: it requires the continuous interaction of various stakeholders and making co-creation more participatory. Several factors influence the sustainability of co-creation processes in the public sector, in particular, capacity building, continuous learning, and training (Edelmann and Virkar 2023). The ethical dimension of co-creation is another underrepresented area that has only recently been addressed by authors (Edelmann et al. 2023; Edelmann and Voigt 2024). The ethics of using TA for co-creation processes and outcomes represent a key aspect of any theory, framework, strategy, and finally, policy.

Furthermore, our study suggests several *avenues for potential future research* that could deepen the findings of the current study and expand understanding in the public service co-creation area.

Avenue for future research 1: Each co-creation project is very context-dependent, so it may not be possible to apply all the recommendations made. There is a need for more extensive research with specific practice-oriented case studies that improve understanding of the contextual features of individual public services and the stakeholders involved. The proposed research framework can be tested in *various application scenarios* to extend the research framework by more concrete structural or procedural aspects.

Avenue for future research 2: Our study is based on (Linders 2012), who considers three co-creation phases. However, there are a number of further approaches to co-creation, that include more or different phases. e.g. by the (Lisbon Council 2021), (Scupola and Mergel 2022) or a more holistic approach based on interrelated actions (Stickdorn and Schneider

2012). Additional research should *compare theories of co-creation* and *co-production* in the context of TA techniques support.

Avenue for future research 3: As noted by (Edelmann and Virkar 2023), co-creation must be distinguished as a process and an outcome. However, this differentiation is not always clearly highlighted in co-creation research. On the basis of our study, we suggest the application of TA to the process of co-creation. However, it is worth considering and analyzing how the use and value of TA can play both in co-creation *processes* and *outcomes*.

Avenue for future research 4: As mentioned in (Barile et al. 2020), there is a need to move from researching co-creation to implementing it. Therefore, we suggest exploring existing worldwide educational offerings and developing an *interdisciplinary educational framework* of the required knowledge and competencies necessary for the successful and effective use of TA methods in sustainable co-creation processes and outcomes.

The identified research gaps and avenues for potential future research point toward new opportunities for rigorous investigation and practical development within the TA-enabled public service co-creation emerging field.

6.1 Limitations

Our research provides solid insights into the application of TA for co-creation in public sector organizations, but it is important to acknowledge several limitations that may impact the generalizability and robustness of our findings. One significant limitation of this study is the *inclusion criteria* applied, which focuses primarily on academic and commercial studies that introduce TA concepts, research methodologies, models, and practical applications in public services across various areas (using the “public service” keyword in our search strategy). Consequently, numerous TA techniques that could potentially enhance the co-creation of public services and engage diverse stakeholders were excluded because their application has not yet been substantiated through research or practice in the public services area. For example, methods like “smoke term” analysis have been suggested for product safety oversight (Goldberg and Abrahams 2018; Nasri et al. 2018; Sithipolvanichgul et al. 2020). These methods represent a form of content analysis and text classification tailored for regulatory market surveillance. They leverage consumer feedback– sourced from online reviews, discussion forum posts, YouTube videos, etc.– to identify product safety issues that could trigger product recalls, legislation, public advisories, or government policies. Despite their potential, this study did not investigate the possibility of using TA techniques, previously applied only in other service sectors, to support the co-creation of public services. As highlighted in Avenue for Future Research 9, there is a pressing need to broaden the scope of research in this direction.

Further, the *quality* and *heterogeneity* of the studies included in our review may vary, which could affect the reliability and validity of our synthesis. While efforts were made to ensure rigour in study selection and data extraction, differences in methodologies, sample sizes, and research contexts may introduce biases or limitations in our analysis.

Additionally, the field of text analytics is *rapidly evolving*, with new techniques, tools, and applications continually emerging. Our review provides a snapshot of the current literature, but future developments in TA may render some of our findings outdated or incomplete. Similarly, the practice of co-creation in public sector organizations is subject to ongoing changes influenced by societal, political, and technological factors.

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Data availability No datasets were generated or analysed during the current study.

Declarations

Conflict of interest The authors declare no competing interests.

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