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Covid-19 sentiments in smart cities: The role of technology anxiety before and during the pandemic

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ABSTRACT

The spread of Covid-19 profoundly changed citizens' daily lives due to the introduction of new modes of work and access to services based on smart technologies. Although the relevance of new technologies as strategic levers for crisis resolution has been widely debated before the pandemic, especially in the smart cities' context, how individuals have agreed to include the technological changes dictated by the pandemic in their daily interactions remains an open question. This paper aims at detecting citizens' sentiment toward technology before and after the emergence of the Covid-19 pandemic using Fuzzy Formal Concept Analysis (FFCA) to analyze a large corpus of tweets. Specifically, citizens' attitudes in five cities (Berlin, Dublin, London, Milan, and Madrid) were explored to extract and classify the key topics related to the degree of confidence, familiarity and approval of new technologies. The results shed light on the complex technology acceptance process and help managers identify the potential negative effects of smart technologies. In this way, the study enhances scholars' and practitioners' understanding of the strategies for enabling the use of technology within smart cities to manage the transformations introduced by the health emergency and guide citizens' behaviour.

1. Introduction

The spread of the Covid-19 redefined organizational strategies, citizens' daily lives, and the interactions between organizations and users by introducing new ways of working and providing (public, educational, mobility) services. Thus, even if the effects of the global crisis cannot yet be assessed and measured definitively, smart technologies can be considered one of the key factors in managing emergencies.

The relevance of new technologies as strategic levers for the development of urban areas and the improvement of city management (Kunzmann, 2020; Costa & Peixoto, 2020) has been investigated in smart cities context. Smart cities are instrumented, interconnected, and intelligent urban areas (Harrison et al., 2010) that pursue shared growth through an integrated set of technologies that shape interactions between actors (Nam & Pardo, 2011). In today's complex scenario, the role of the smart cities (and of their human resources and technology) as leading actors to face Covid-19 and future pandemics has been highlighted to challenge the global emergency. Even before the pandemic, smart technologies contributed to redesign the configuration of urban spaces. However, despite the revolutionary role of technology in smart cities, it has been noticed that intelligent tools do not automatically allow the achievement of well-being and innovation (Lytras et al., 2020). Adopting technology could be necessary but not a sufficient condition for the effective readaptation and redefinition of the organizational models imposed by the desire to overcome the health emergency. Human interaction with technology is mediated by the political and institutional context in which the technologies are implemented (Kummitha, 2020). The most recent contributions in literature highlight the need to explore how humane smart cities can help manage critical issues in the administration of smart cities through entrepreneurship, governance, and citizens' inclusion (Kitchin. 2015; Visvizi et al., 2018). Moreover, individuals and organizations do not always own the right digital skills or the right propensity towards adopting new technologies (Azoulay & Jones, 2020). Recent studies show that technology use may also have negative implications on users' wellbeing by determining stress toward applying ICT (*information and communication technologies*) to daily lives (Hauk et al., 2019; Nimrod, 2018). To fully integrate technologies into their habits and routine, users should learn to manage technological tools. In addition, they should refocus their cognitive strategies to accomplish the cultural and social requirements related to their use.

The economic, relational, and social transformations determined by

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the different strategies implemented to attain an active resolution of Covid-19 can change, probably definitively, the nature of interactions and collaborations between citizens and public organizations by emphasizing that the application of human intervention (e.g., attitude, adhesion, propensity, smart orientation and willingness to use technologies of individuals-citizens) is the only way to use technology effectively to manage unexpected phenomena (Kunzmann, 2020). For these reasons, there is the need to explore whether and how individuals-citizens have agreed to include the technological changes dictated by the pandemic in their daily interactions by changing their habits and remodeling behaviours and attitudes. Detecting citizens' sentiment toward technology can permit to clarify the current directions of technology acceptance. Furthermore, it could support exploring the (social, economic, psychological) barriers to using technology and removing them to tackle the pandemic or other similar future emergencies by turning crises into opportunities for innovation and improvement of public services. As an economical, social, and political global epidemic, Covid-19 should be studied to support healthcare management and capture all the shades (e.g., distress, anxiety, fear) of its psychological and behavioural consequences (Abd-Alrazaq et al., 2020). Recent research emphasizes the urgency to define the drivers of a digital mental health revolution that can support citizens in managing pandemics through e-services platforms and mobile applications.

This study explores citizens' attitudes toward technology (and the technological transformation determined by Covid-19) through public sentiment analysis. In this way, the goal of the empirical research is to assess the degree of the propensity to use technology employing the variables and indicators of technology anxiety scale (Meuter et al., 2003; Tarafdar et al., 2007), which operationalizes the key factors and stimuli that induce stress in the use of ICT. Thus, two research objectives are pursued: 1) to explore citizens' sentiment towards the adoption of technologies to challenge Covid-19 by detecting their degree of technology anxiety; 2) to reveal the change of attitude and behaviour toward technology by comparing the different variations of technology anxiety before and after the advent of the pandemic. The empirical research analyses the different citizens' sentiment in selected European smart cities, of which-following Brexit-four are European Union (EU) member-states (Berlin, Dublin, London, Milan, and Madrid). In detail, the attitude toward the changes induced by Covid-19 is analyzed by detecting citizens' sentiment towards a series of topics related to the use of the new digital tools, facilities, and services from an emotional and linguistical point of view in the pre- and post-pandemic period. The five cities have been selected based on their size, level of smartness, and strategic influence in Europe and, thus, based on their representativeness of contemporary urban trends.

Tweets' analysis is performed through the Fuzzy Formal Concept Analysis (FFCA) to build a fuzzy concept lattice identifying the critical factors in using technology that receives most users' comments. The methodology allows the detection of the most recurring topics related to users' technology anxiety in different periods by comparing the public sentiment of other cities worldwide. Then, regression analysis is realized to assess if the trends of technology anxiety can help understand the changes of attitude before-after the pandemic as a binary dependent variable. The findings permit introducing a framework that classifies the different determinants of public sentiment related to the anxiety in using technology and the various opportunities and challenges for each area.

The paper is structured as follows. Section 2 reviews previous works on the topic of technology use in smart cities and on technology anxiety. Section 3 describes the methodological approach followed (i) to identify the most recurring features of technology anxiety and (ii) to observe the variations in technology anxiety before and after the diffusion of Covid-19. The findings are debated (paragraph 4) and then synthesized to design a conceptual framework with the key determinants of technology anxiety in the discussion (paragraph 5). Finally, in the last two paragraphs, the theoretical and managerial implications and the conclusion of the study are discussed.

2. Literature review and theoretical background of the study

The current section presents and critically debates the related works that explore the relationship between technology and people in smart cities by revealing the main criticalities in the adoption of ICT and ITs-enhanced urban infrastructure. After the state of art analysis on smart cities and technology anxiety, identifying some gaps in extant research permits to derive the research objectives. Hence, the last paragraph describes the need to detect users/citizens' abilities to use, accept, and integrate technology into their lives to reduce technological anxiety sources and fully accept the technological, social, and cultural changes introduced by disruptive technologies.

2.1. Smart cities and technology: origins and latest developments

For about twenty years, the concept of "smart city" has received increasing attention in urban planning and governance (Nam & Pardo, 2011; Visvizi, & Lytras, 2018, 2019). As broadly discussed in the literature, a smart city can be defined as complex sets of technology (infrastructures of hardware and software), people (creativity, diversity, and education), and institutions (governance and policy) (Nam & Pardo, 2011). Smart cities should be explored according to an all-inclusive perspective that does not overrate the technological dimension but that considers the economic, social, governmental, and environmental dimensions (Stratigea, 2012; Albino et al., 2015; Neirotti et al., 2014) as a set of integrated enabling factors for urban and service improvement. In such a scenario, smart cities can create a fertile environment to drive innovation from a technological, managerial, and organizational point of view by fostering environmental and social wellbeing (Karvonen et al., 2018; Polese, 2021).

Therefore, creating effective and really "smart" cities can be considered a key lever for community welfare. Smart city networks can provide suitable instruments to empower data sharing in outbreaks or disasters, leading to better global understanding and management of emergencies (Allam & Jones, 2020). The development of more efficient and widespread smart city initiatives can improve the way critical data is retrieved, processed, stored, and disseminated, potentially improving the detection and mitigation of outbreaks while reducing the execution time when taking critical actions (Costa & Peixoto, 2020). Smart city approaches can drive individuals to use data and knowledge on vulnerable groups and poor urban areas to support the social and economic crisis (Söderström, 2020). Accordingly, the increasing use of ICTs has improved the internet of things applications in healthcare and citizen participation for epidemic detection during Covid-19 (Giffinger et al., 2007; Abusaada et al., 2020). In this way, the multiple technological points and their real-time ability to collect and share data can significantly improve well-being and quality of life by strengthening citizens' involvement in policymaking (Vanolo, 2016) and generating added value and crisis response capacity in the urban context (Lytras, Visvizi, & Jussila, 2020).

In light of recent global events, implementing new technology in smart cities (Abusaada & Elshater, 2020) requires an integrated infrastructure to detect and prevent a public health emergency (Costa & Peixoto, 2020). Several digital solutions have been developed during the pandemic to implement a strategy to contain the virus spread, monitor human stress, and collective wellbeing, and collect complex space-time events in a smart city related to Covid-19 safety measures (Basmi et al., 2021). As happened in several smart cities, the proper combination of a contact-tracing app, robots, and digital thermal-gantries put in place by the government to trace, track and mitigate the early first wave of the pandemic along with the civil society involvements to manage the spread of the virus proved essential for containing the pandemic crisis (Söderström, 2020).

Hence, advanced technology can mitigate the negative effects due to the pandemic by permitting people to continue their lives while maintaining social distancing (Jaiswal et al., 2020). However, citizens, governments, and organizations do not always own the right digital skills or the right propensity to adopt new technologies (Azoulay & Jones, 2020). In this scenario, further research efforts are needed to understand how citizens and individuals have agreed to include the technological changes dictated by the pandemic in their daily interactions.

2.2. Public sentiment in smart cities as a predictor of citizen behaviour

The pace of technological, economic, and social changes dictated by the global emergency leads to rereading human-computer interactions and rethinking the rules that guide citizen behaviours in smart cities. However, the top-down adoption of technology in urban contexts cannot ensure growth and innovation and the effective and sustainable transformation of cities. Hence, city managers and policymakers should engage citizens in reframing spaces, habits, and routines in urban life and should constantly assess their attitude toward technology, their digital mindset, and their acceptance of the new solutions proposed (Wnuk et al., 2020).

It follows that the exploration of citizens' perception and opinion about the administration of public life, the introduction of new technologies, and the general management of worldwide crisis (Chen et al., 2020) is a strategic lever to understand and predict people's behaviours and compliance with the new rules introduced and, consequently, to evaluate the effectiveness of urban policies. Furthermore, the services and the applications offered in smart cities should be aligned to users' needs, expectations, and abilities to use these services and applications efficiently (Visvizi et al., 2020).

Coronavirus and global crisis, in general, can entail the development of mass fear and panic accentuated by inaccurate information. Therefore, there is the need to examine public sentiment in the Covid-era to constantly monitor the effects of government measures and regulations, evaluate the degree of technology adoption, and undertake timely decisions and corrective policies in the management of pandemics (Samuel et al., 2020).

The use of textual data (Tweets) for sentiment analysis can fulfill the need to monitor the flow of information and the development of mass sentiment in a fast-changing setting characterized by the rapid and uncontrollable spread of Covid-19. The analysis of public opinion and the identification of topics and trends (Hung et al., 2020) permit tracking the progress of fear toward the virus itself and toward the use of technology and to forecast future scenarios and the developments of the crisis.

Investigating public sentiment associated with the diffusion of Covid-19 seems to be a priority in contemporary research. The exploration of citizens' discussion about Covid-19 can reveal unnoticed sentiments and trends related to people's acceptance and personal management of the changes imposed by the pandemic. For this reason, a series of recent studies adopt sentiment analysis (Hung et al., 2020; Samuel et al., 2020; Shah et al., 2019) to explore the textual data obtained from the collection of the thoughts expressed through social media posts to assess public opinion.

2.3. Technology anxiety: assessing citizens' attitudes and behaviour during global emergency

The disrupting impact of Covid-19 on smart cities requires understanding citizens' sentiment and perceptions of governmental measures and the estimation of the effects of a pandemic on individuals' views (Al-Hasan et al., 2020) and people's degree of frustration and stress. As discussed above, citizens' behaviour (and their ability to adapt to environmental changes) can be critical determinants for successfully implementing services, applications, and new technological solutions in smart cities.

To explore the key drivers and obstacles to the acceptance of technology in smart cities, *technology anxiety* (Compeau et al., 1999; Meuter et al., 2003; Washizu et al., 2019) can be assessed as a predictor of citizens' behaviour and as a significant determinant of behavioural intention (Yang & Forney, 2013) in Covid-era. Technology anxiety is defined as a complex set of emotions such as nervousness, uncertainty, and fears associated with using and learning to use technology. This concept is related to apprehension about the negative consequences of using technology, such as losing important data or making mistakes (Compeau & Higgins, 1995). It involves both the (objective) lack of technological skills and the (subjective) low confidence in their abilities to use specialized tools. In addition, it can be related to the user's state of mind about general technology tools (Meuter et al., 2003) or to hidden social and psychological factors, such as cost concerns, dependency concerns, trust in technology providers and organizations adopt technology, privacy concerns.

The need to explore technology anxiety in contemporary contexts stems from recognizing this variable as a determinant of resistance to technology and as a barrier to individuals' involvement with technology (Thatcher & Perrewé, 2002). Moreover, anxiety can lead to rejection of technology and technophobia (Daruwala, 2020), a negative durable emotional reaction towards ICT, and technostress (Ragu-Nathan et al., 2008), a general distressful state caused by technology (Nimrod, 2018).

Technology anxiety (also known as TISA, Technology Induced State Anxiety) has been conceptualized in literature (Meuter et al., 2003) as a negative affective state toward technology that affects the relationship between people and technology (Zhang, 2013). Hence, differently from the concepts of technostress (Ayyagari et al., 2011; Tarafdar, Gupta, & Turel, 2013) or general computer anxiety (Heinssen et al., 1987; Tekinarslan, 2008), this construct defines a temporary state deriving from environmental turbulences (such as the advent of global emergencies) and permits to observe in-depth the individual psychological reactions to technology rather than analyzing a more "general" behavioural aspect. For this reason, it seems to be a more easily generalizable concept that can also be used outside the business context. Moreover, technology anxiety allows the exploration of the development of negative emotions and fear as consequences of the introduction of a given technology by evaluating the emotional state of individuals and not the acceptance and use of technology per se (e.g., such as the technology acceptance model, Davis, 1989). Thus, investigating the degree of technology anxiety in contemporary cities can shed light on the different emotional shades of public sentiment and citizens' behaviors.

The development of technology anxiety in smart cities can prevent the inadequate usage of technology and play a vital role in adopting smart services. Revealing how technology anxiety can take shape in the smart cities of Covid-era can help policymakers assess the needs of stakeholders in an appropriate and relevant manner by understanding how crisis can be managed through the inclusion of citizens in the co-development of innovative solutions to address social change.

2.4. Background of the research

Despite the increasing diffusion of the analysis of the opportunities and challenges in adopting technology to face pandemics in smart cities, two main issues emerged from the brief overview conducted above. Firstly, there is the need to explore the weight of human capital in the use of ICT: citizens' digital culture, their attitude toward technology (Hollands, 2008; Mora et al., 2017), and their propensity to change their lives through technology-mediated interactions (Kunzmann, 2020). Secondly, future research must shed light on the negative effects that technology can have on citizens' wellbeing and identify the obstacles of the acceptance and adhesion to smart technologies and of their advantageous application (Hollands, 2008; Hauk et al., 2019; Mora et al., 2017; Nimrod, 2018).

Therefore, the true turning point for the resolution of a pandemic would also concern citizens' behaviour by referring to their acceptance of technological changes, their willingness to use technology to reframe their lives, and in the removal of psychological barriers (privacy concerns, perception of inability, etc.) for employing technology successfully and solving the socio-economic crisis introduced by a public health emergency. For this reason, albeit the relevant literature highlighted the potential of smart technologies during the pandemic, contemporary debate on smart cities should explore how relationships between people and technologies can be redesigned to identify the most adequate strategies to involve citizens in the active resolution of the crisis and global emergency and to co-develop innovative solutions and social changes, which still represents an open question. To address the first gap identified in literature on smart cities (the lack of studies on the key role of users'/citizens' attitude as an enabling factor of wise use of technology, cf. paragraph 2.1), this study explores the public sentiment of citizens during the public health emergency as a predictor of their potential behaviour and its possible variations. Despite the increasing diffusion of research that examines the public reaction to the contemporary health emergency, a deep understanding of the most common themes, concerns, and sentiments related to the perception of Coronavirus has not been achieved yet. This study analyzes citizens' sentiment shared through Twitter, one of the most popular microblogging platforms, with over 350 million users and 152 million daily users who produce 500 million tweets a day (Statista, 2020). Microblogging is a quick communication means that can capture tweeters' perception at any moment and can help to catch insights into their attitudes and opinion on the usefulness and usability of specific smart-city services and applications (Oulasvirta et al., 2010).

To bridge the second gap (the absence of studies that conceptualize the critical obstacles to the acceptance of technology), *technology anxiety* (Compeau et al., 1999; Meuter et al., 2003; Washizu et al., 2019) can be assessed as a predictor of citizens' behaviour and as a significant determinant of behavioural intention (Yang & Forney, 2013) in Covid-era.

This study explores the degree of acceptance and inclusion of smart technologies into citizens' daily lives by using technology anxiety as an indicator of adhesion to the measures imposed by the public health emergency, participation, inclusion, and willingness to adopt new technologies.

The measurement of this construct has been proposed in extant quantitative research through a re-adaptation of the computer anxiety scale, developed by Ceyhan & Namlu (2000). As Table 1 shows, the key sub-dimensions and items of technology anxiety refer to (i) users' confidence in their capability to use technology; (iii) ICT pressure, lack of technical support, and low usability of technological tools; (ii) economic risk; (iii) perceived uselessness of technologies; (iii) privacy concerns (Ayyagari et al., 2011; RaguNathan et al., 2008). Starting from the synthesis of the measurement items deriving from the scales introduced in extant research (Meuter et al., 2003; Washizu et al., 2019; Lytras et al., 2021), some key indicators are obtained and employed as keywords to extract tweets, filter the analysis and guide the interpretation of results (see paragraph 4).

The sub-dimensions related to self-confidence, user's perception of their ability to use technology, and fear have been borrowed from Meuter et al. (2003) to explore the apprehension of citizens in the use of technology and the potential lack of confidence in their capability that can create concern about the coping ability to deal with new and demanding situations (Schwarzer et al., 1999).

The items for the sub-dimensions of apprehension, scare, and mistake are re-adapted from Washizu et al. (2019) and Chen et al. (2020) to explore citizen psychological concerns during the crisis predict their reactions to unexpected phenomena and their self-resilience in response to disrupting events.

The items re-adapted from Lytras et al. (2021) refer mainly to three dimensions: economic, knowledge-based, and social. The first aims at detecting users' worries about the return on investment and the financial sustainability of smart-cities services. The second refers to exploring one of the key levers of cities growth (and, consequently, one of the key obstacles in case of lack), knowledge development, and the sharing of

Table 1
The identification of keywords for a tweet analysis on technology anxiety.

Authors	Measurement Items	Keywords
Meuter et al. (2003)	I am confident I can learn technology-related skills.	SKILLS CONFIDENCE
	I have difficulty understanding most technological matters.	DIFFICULTY UNDERSTANDING
	I feel apprehensive about using technology.	APPREHENSION
	When given the opportunity to use technology, I fear I might damage it in some way.	FEAR DAMAGE
	I am sure of my ability to interpret technological output.	ABILITY
	Technological terminology sounds like confusing jargon to me.	CONFUSION
	I have avoided technology because it is unfamiliar to me.	UNFAMILIARITY
	I am able to keep up with important technological advances.	DEAL WITH
	I hesitate to use technology for fear of making mistakes I cannot correct.	MISTAKE
Washizu et	I feel apprehensive about using technology.	APPREHENSION
al. (2019) Chen et al. (2020)	It scares me to think that I could cause technology to destroy a large amount of information by hitting the wrong key	SCARE
	I hesitate to use a computer for fear of making mistakes I cannot correct	MISTAKE
	Computers are somewhat intimidating me	INTIMIDATING
Lytras et al. (2021)	Smart city services make me anxious about my ability to use technology	ANXIOUS ABILITY
	I think that a lot of money is spent on smart city services without them offering anything significant to the society and individuals	MONEY SOCIETY USEFULNESS
	I think that we lack the basic infrastructure in the city and, so, smart city services are a pointless luxury	LACK INFRASTRUCTURE
	I feel that smart city services offer organizations a good excuse to manage my personal data, and I don't like it	PERSONAL DATA PRIVACY
	I think that, on average, people my age lack the skills and nerve to use these services	SKILLS

information and learning capabilities (Visvizi et al., 2018). Lastly, the third sub-dimension considers the social impact of smart cities applications by investigating privacy, safety, and security issues (Chui et al., 2018) and users' perception of transparency in the data processing methods used (Perez del Hoyo and Mora, 2019).

Two research objectives are pursued. In the first place, the themes (topics) connected with the mentions of the key indicators of technology anxiety on Twitter are detected through sentiment analysis; in the second place, the potential change in the perception of the different subtopics deriving from technology anxiety is revealed through regression analysis, by estimating the reduction or the increase in the degree of technology anxiety before and after the advent of the pandemic. As a result, the following research questions can be introduced:

RQ1: Which are the most common topics associated with technology anxiety in the public sentiment of citizens from five international smart cities (Berlin, Dublin, London, Milan, and Madrid)?

RQ2: How did citizens' sentiment toward technologies change after the advent of Covid-19?

3. Methodology

In this study, the research method develops a content analysis of tweet stream by applying the Text-Mining process and conceptual data analysis techniques. The following subsections introduce the Fuzzy Formal Concept Analysis (briefly, Fuzzy FCA or FFCA, De Maio et al.,

2012) and Association Rules Mining. Finally, the description of the application of these techniques to the overall workflow for analysing tweets content underlying this study is given.

The Fuzzy FCA is used to extract the hierarchy (the lattice) of Formal Concepts, grouping tweets with the same main features. Finally, the Association Rules Mining extracts the dependence among the concepts intents (i.e., most co-occurring keywords and emotional features) and the technology anxiety in the pre-/post- Covid contexts.

3.1. Fuzzy FCA

Fuzzy FCA deals with fuzzy relations between objects (e.g., tweets, etc.) and their features (e.g., keywords, sentiment polarity, etc.) considering membership varying in (0, 1), instead of binary relation of traditional FCA (Ganter & Wille, 2012). So, it allows specifying more or less relevant features to represent resources, enabling the granular representation.

Formal Concept Analysis (FCA) is a mathematical theory suitable for several application domains, such as knowledge discovery, ontology learning, text mining, bioinformatics, etc. Its fuzzy extension provides more accurate data mining and data summarization to deal with the uncertainty of data representation, like in the content of the tweets. Among other data mining techniques and machine learning tools, Fuzzy Formal Concept Analysis (FFCA) is the most suitable in our case because it provides transparent and intelligible results.

The resulting Fuzzy Concept Lattice is a hierarchical knowledge structure that could be easily explored by filtering meaningful concepts for answering some research questions. Moreover, it provides valuable measures evaluating the confidence of the extracted entails. Despite other techniques, it also works if data are not so massive and relies on the meaningful hierarchical knowledge structure instead of black-box-based approaches more suitable for obtaining high performance not required in our case. More in detail, the FFCA in this work is used to extract the hierarchy (the lattice) of Formal Concepts, grouping tweets sharing the same main features. The Association Rules Mining carries out the dependence among the concepts intents (i.e., most co-occurring keywords and emotional attributes) and the technology anxiety in the pre-/post- Covid contexts. These results allow us to explore the dependence among factors we are investigating.

Following, some definitions of Fuzzy FCA are given.

Definition 1: A Fuzzy Formal Context is a triple $K=(G, M, I)$, where G is a set of objects, M is a set of attributes, and $I=((G\rightarrow M), \mu)$ is a fuzzy set. Recall that, being I a fuzzy set, each pair $(g,m)\in I$ has a membership value $\mu(g,m)$ in $(0,1)$. In the following, the fuzzy set function μ will be denoted by μI.

Definition 2: Fuzzy Representation of Object. Each object O in a fuzzy formal context K can be represented by a fuzzy set $\phi(O)$ as $\phi(O)=\{A1(\mu_1), A2(\mu_2), \ldots, Am(\mu_m)\}$, where $\{A_1, A_2, \ldots, A_m\}$ is the set of attributes in K and μ_i is the membership of O with attribute A_i in K. $\phi(O)$ is called the fuzzy representation of O. Unlike FCA that uses binary relation to represent formal context, Fuzzy Formal Context enables to model relations among objects and attribute in a more smoothed way, ensuring more precise representation and uncertainty management. Fuzzy Formal Context (see Definition 1) is often represented as a cross-table, as shown in Fig. 1(a), where the rows represent the objects, while the columns the attributes. After establishing a confidence threshold (e.g., $T=0.6$), only the relationships with a membership value greater than it is considered for the lattice construction (as the case in Fig. 1).

Given Fuzzy Formal Context, the Fuzzy FCA algorithm can identify Fuzzy Formal Concepts and subsumption relations among them. More formally, the definition of Fuzzy Formal Concept and order relation among them are given as follows:

Given a fuzzy formal context $K=(G,M,I)$ and a confidence threshold T, for $G'\subseteqq G$ and $M'\subseteqq M$, we define $G^*=\{m\in M \mid \forall g\in G', \mu_I(g,m)\geq x\}$ and $M^*=\{g\in G \mid \forall m\in M', \mu_I(g,m)\geq x\}$

Definition 3: Fuzzy Formal Concept. A fuzzy formal concept (or fuzzy concept) C of a fuzzy formal context K with a confidence threshold x, is $C=(I_{G'}, M')$, where, for $G'\subseteqq G$, $I_{G'}=(G', \mu)$, $M'\subseteqq M$, $G^*=M'$ and $M^*=G'$.

Each object g has a membership $\mu_{IG'}$ defined as

$$\mu_{IG'}(g) = \min_{m\in M'}(\mu_I(g,m)) \quad (1)$$

where μ_I is the fuzzy function of I.

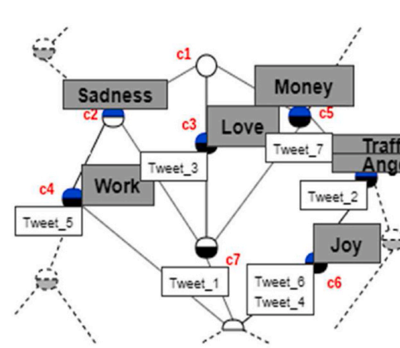
Note that if $M'=\varnothing$ then $\mu_I(g)=1$ for every g. G' and M' are the extent and intent of the formal concept $(I_{G'}, M')$, respectively.

Definition 4: Let $(I_{G'}, M')$ and $(I_{G''}, M'')$ be two fuzzy concepts of a Fuzzy Formal Context (G, M, I). $(I_{G'}, M')$ is the subconcept of $(I_{G''}, M'')$, denoted as $(I_{G'}, M')\leq(I_{G''}, M'')$, if and only if $I_{G'}\sqsubseteq I_{G''}$ $(\leftrightarrow M''\subseteqq M')$. Equivalently, $(I_{G''}, M'')$ is the super concept of $(I_{G'}, M')$.

For instance, in Fig. 1(b), concept c_7 is a subconcept of concept c_3. Equivalently the concept c_3 is a super concept of concept c_7. Let us note that each node (i.e., a formal concept) is composed of the objects and the associated set of attributes, emphasizing the object that is better represented by a set of attributes by means of fuzzy membership. In the figure, each node can be colored differently, according to its characteristics: a half-blue colored node represents a concept with its attributes; a half-black colored node instead outlines the presence of own objects in the concept; finally, a half-white colored node can represent a concept with

	Money	Work	Love	Joy	Traffic	Sadness	Anger
Tweet_1	**1.00**		**1.00**			**0.61**	0.58
Tweet_2	**0.72**	0.25	0.35	0.35	**0.94**		**0.94**
Tweet_3			**0.97**	0.52	0.31		0.56
Tweet_4	**0.93**			**1.00**	**0.80**		**0.64**
Tweet_5	0.40	**0.96**				**0.78**	
Tweet_6	**0.65**		0.57	**0.70**	**0.70**		**0.61**
Tweet_7	**0.60**			0.58	0.55		

(a) Fuzzy Formal Context



(b) Fuzzy Formal Concept Lattice

Fig. 1. Examples of (a)Fuzzy formal context and (b)Fuzzy formal concept lattice.

no own objects (if the white-colored portion is the half below of the circle) or attributes (if the white half is up on the circle). Furthermore, given Fuzzy Formal Concepts of Fuzzy Formal Context, it is easy to see that the subconcept relation $\leq$ induces a Fuzzy Lattice of Fuzzy Formal Concepts. The lowest concept contains all attributes, and the uppermost concept contains all objects of Fuzzy Formal Context.

3.2. Association Rules Mining

Association Rules aim to intercept co-occurrence implications among itemsets. Their most popular application regards the market basket analysis that studies co-occurrences in transactions. The metrics, such as Support and Confidence, measures the strength of associations. Several algorithms are applied for Association Rules Mining (e.g., Apriori, FP-growth, etc.) in the literature. In this study, the algorithm for mining Association Rules exploits the hierarchical relationships among concepts in the lattice resulting from the application of Fuzzy FCA.

Given a Formal Context $K = (G, M, I)$ consisting of attributes $M = m_1, m_2, \ldots, m_m$ and objects $G = g_1, g_2, \ldots, g_n$, an association rule is an implication of the form $X \Rightarrow Y$ where $X, Y \subset G$ are sets of attributes and $X \cap Y = \emptyset$. The algorithm extracts Association Rules where X, Y are the formal concepts intents in subsumption relation (see subconcept/super concept in the Definition 4).

The relevance of each Association Rule is measured by support and confidence. The support of an association rule $X \Rightarrow Y$ is the percentage of objects (i.e., tweets in this study) that contain $X \cup Y$. The *confidence* of $X \Rightarrow Y$ is the ratio of the number of objects containing $X \cup Y$ to the number of objects that contain X. More formally:

Definition 5. Being M is a set of attributes of a formal context $K = (G, M, I)$. An association rule is a pair $X \Rightarrow Y$ with $X, Y \subseteqq M$. The support is defined as:

$$\sup(X \Rightarrow Y) = \frac{|(X \cup Y)'|}{|G|}$$

where (.)' is the derivation operator. The confidence is computed as:

$$\mathrm{conf}(X \Rightarrow Y) = \frac{|(X \cup Y)'|}{|(X)'|}$$

In the lattice retrieved by Fuzzy FCA, the concepts frequently recurring in the collected tweets are measured using the Support indicating how frequently the itemset (i.e., concepts' intents) appears in the tweets collection. *Confidence* indicates how often the itemset (i.e., concepts' intents) of features characterizing the tweets occurs under interest conditions. Indeed, *confidence* can be interpreted as an estimate of the conditional probability $P(Y|X)$.

3.3. Overall workflow

The main goal of the analysis is to represent tweets based on their text contents and then assess words trend to understand citizens' sentiment and perception of the evaluated smart cities in the pre- and post-Covid periods. The five cities included in the analysis (Berlin, Dublin, London, Madrid, and Milan) have been selected through emergent sampling (Shakir, 2002; Teddlie & Yu, 2007), a case selection procedure in which sampling decisions are undertaken during the process of data collection. As researchers gain more knowledge of a setting, sampling decisions that take advantage of events can be made. This flexible sampling design is used when little is known about a phenomenon or a set, and a priori sampling decisions can be difficult. In this case, the number of citizen's tweets on the key topics of technology anxiety for the different international cities was not predictable before the analysis; thus, after a preliminary screening of the datasets, the cities with the highest number of tweets on the keywords selected have been incorporated in the sample.

The Fuzzy Formal Concept Analysis allows extracting a hierarchy (i.e., lattice) of concepts representing objects (i.e., tweets) and their attributes (i.e., words, emotional features, and sentiment). The Support associated with each lattice concept allows measuring how frequently the itemset (i.e., concepts' intents) appears in the tweets collection. Additionally, by browsing the resulting Fuzzy Lattice, we retrieve the dependence degree among concepts' intents (i.e., most co-occurring keywords and emotional features) and the use of technology in pre-/post- Covid contexts. *Confidence* of the Association Rules indicates how often the linguistical and emotional features co-occurring when the conditions of interest occur. The conditions (or condition) of interest may be represented by pre- or post-Covid context or/and by the smart cities we are considering. By comparing citizens' sentiment toward the different international smart cities before and after the emergence of the pandemic, the complex process of accepting the limitations dictated by the health emergency and the potential improvement of fear and sentiment over time can be assessed.

Overall methodology (in Fig. 2) consists of the following activities:

1. Tweets collection about selected smart cities.
2. Feature Extraction.
3. FFCA & Association Rule Mining.
4. Regression Analysis of the incidence of construct indicators.

Subsequent sections describe in more detail each step.

3.3.1. Step 1: tweets collection about selected smart cities

A web scraper allows collecting tweets responding to query parameters by adopting the Twitter Advanced Search. It complies with Twitter's restrictions in terms of both adoption and privacy concerns. The query search for tweets responding to keywords "smart AND city" posted from January to December 2019 (for the pre-Covid period) and from January to November 2020 (for the post-Covid period, which includes the first wave of lockdowns in Spring 2020 and the beginning of the second wave in October 2020).

About 41K tweets are retrieved. Through a filter based on indicators related to identified constructs (e.g., virus, money, infrastructure, transport, etc.), only more relevant tweets are kept for a total of 32′334 tweets by 22′202 users (with 17′579 replies and no retweets). The pre-Covid period has 17′204 tweets while the post-Covid, 15′130. The distribution among cities is as described in Table 2.

3.3.2. Step 2: feature extraction

The feature extraction activity applies a pipeline to descriptions of collected tweets. The objective is to extract attributes characterizing tweets for the subsequent process of FFCA. More in detail, the Receptiviti API[1] is adopted to extract emotional components from the text (e.g., joy, sadness, fear, etc.). Then, a Natural Language Processing pipeline consisting of tokenization, POS tagging, lemmatization, stemming, stopwords removal, and synonyms analysis is applied. Next, a sentiment analysis extracts the polarity of adopted tweets. Finally, keywords are selected as attributes of the Formal Context in the next step.

3.3.3. Step 3: FFCA & Association Rule Mining

Keywords extracted during the previous phase fill the formal context needed for constructing the Fuzzy Formal Concept Lattice. In particular, for each selected smart city, the Formal Context contains a row for each tweet (i.e., objects of the context) mentioning it. Attributes are composed of the most important terms (i.e., keywords), sentiment polarity, emotional components, and period (i.e., pre- or post- Covid). The membership of each attribute is set to 1, except for emotional components for which the membership corresponds to the API's value.

The fuzzy formal concept lattice generated by the formal context is then adopted to extract the frequent itemset consisting of combinations

[1] https://www.receptiviti.com/.

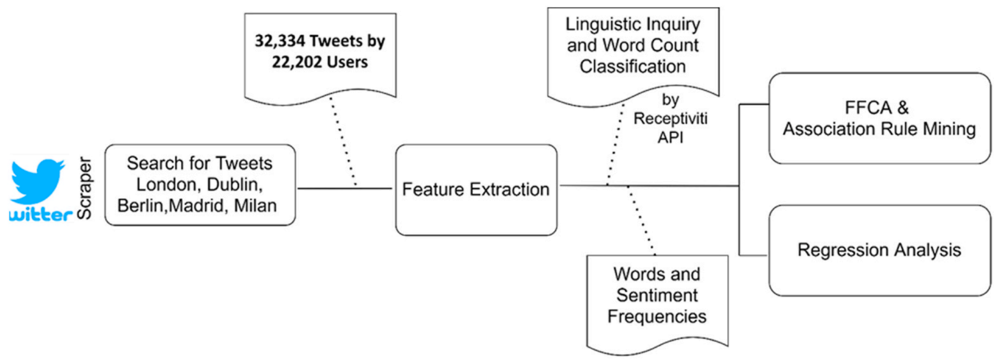


Fig. 2. Overall methodology.

Table 2
Tweets distribution among cities.

City	Tweets
London	18.086
Milan	3.896
Dublin	1.769
Berlin	4.384
Madrid	4.199
Total	32.334

of cited attributes. In particular, using the support value, a measure of confidence is extracted for each "condition of interest"-items couple. Thus, for example, assuming to be interesting in London city, if the condition regards the pre-Covid period and negative sentiment, we can assess the incidence of other attributes (e.g., keywords and emotional conditions).

3.3.4. *Step 4: regression analysis of the incidence of construct indicators*

Finally, the validity and incidence of identified indicators for each construct are also verified by applying a logistic regression algorithm. By considering indicators as independent variables and the period as the dependent variable, we try to identify the period basing on the keywords used in the tweets' contents by the citizens. Thus, for the significant variables (i.e., $p < 0.05$), the coefficient β is evaluated. When β is positive, it indicates the log-odds probability (i.e., an incidence) of the pre-Covid period and a decreasing probability for the post-Covid period.

4. Findings

The empirical research investigates public sentiment (detected through technology anxiety) towards the technological changes required to apply Covid-19 measures (distance learning, smart working, online public services) and the variation in the polarity of this sentiment in the two-time frames considered (before the pandemic and after the advent of the pandemic).

In this way, it is possible to explore the attitude and propensity of citizens to change their lifestyles and their citizenship behaviour to challenge the public health emergency. Furthermore, it is possible to evaluate the different evolution of the attitude towards the changes introduced by Covid-19 in other international smart cities.

To answer RQ1 (see paragraph 4.1), a fuzzy formal concept lattice for each selected smart city is built to estimate the dependence between the most co-occurring keywords and emotional features and the tweets that mention technology anxiety pre-/post-Covid contexts.

To address RQ2 (see paragraph 4.2), the key topics detected through FFCA are used as the independent variables, and the time-lapse of Tweets is treated as a dependent variable in a logistic regression to predict the period (before and after the spread of Covid-19) as the binary dependent variable.

4.1. *Citizens' sentiment of technology anxiety: key topics and emotional features*

Table 3 reports the most common topics and emotional features related to technology anxiety detected by analyzing citizens' sentiment in the five international smart cities investigated (Berlin, Dublin, London, Milan, and Madrid). For each city (see column 1), the words that co-occur most frequently with the key indicators of technology anxiety in users' tweets are detected. The second and the third columns of the Table show the most common topics associated with negative and positive sentiment toward using technology in the posts before the advent of Covid-19. The fourth and the fifth columns reveal the most frequent words associated with negative and positive sentiment toward technology in the tweets generated by users after the spread of Covid-19. Only the attributes with the highest degree of confidence (greater than 0.6), the probability of co-occurrence of the linguistical and emotional features under the conditions of interest, are considered valid for the interpretation and provided in the Table.

4.1.1. *The pre-covid period*

In the pre-Covid period, the prevalent negative sentiment that emerged from citizens' tweets from Dublin, London, Madrid, and Milan is anger. In contrast, the mention of anxiety toward technology is associated most frequently with topics related to fear in Berliners' tweets.

The analysis of the findings reveals that in Madrid, the anxiety is generated from the perception of the inability to use technology and recognize the need to increase knowledge and learn how digital tools should be employed. Therefore, through the co-occurrence of words like "lack", "knowledge", "learn", a lack of self-confidence in technology adoption can be noticed (Anger Knowledge Learn Lack Difficulty Want Care) and a negative user's state of mind regarding the ability and willingness to use technology-related tools can be observed. The Dubliners in the sample also express the difficulty in using technology for private life and the perception of asymmetry and unbalance in the detection of technological power and skills (Anger Hard Business Work Power). This finding is in line with citizens' anxieties about the centralization of the profits deriving from smart services and the lack of social usefulness (Lytras et al., 2021). The shortage of self-confidence to employ technologies is one of the key concerns identified in extant empirical research. The perception of inability is an obstacle to adequate knowledge sharing and skills acquisition (Pérez-delHoyo & Mora, 2019), which can be considered the crucial factors for the success of a smart city (Visvizi & Lytras, 2018).

The analysis of Londoners' tweets reveals that the anger toward the economic exploitation of the advantages deriving from the use of technologies ("money") and the general unsatisfaction toward the use of technology for the fulfilment of personal success (Money Work Anger Business One Sadness). Thus, technological anxiety is related to an individual dimension before the advent of Covid-19; this negative attitude

Table 3
Findings for RQ1: the key topics obtained through FFCA.

	(BEFORE COVID-19) Most frequent words		(AFTER COVID-19) Most frequent words	
Cities	**Negative sentiment**	**Positive sentiment**	**Negative sentiment**	**Positive sentiment**
BERLIN	Fear Technology Data **Difficulty** Platform Network	Future **Build** Citizen Sustain Connect Together Share	Anger Everyone **Power** **Government** Data Interest Support Citizen Listen	**Community** Desire Sustain Want Partner Team System
	Difficulty & Fear	Society	Lack of support	Society
DUBLIN	Anger **Hard** Business Work Power	New Data **Infrastructure** Future Citizen Collaboration IOT Manage Solution	**Fear** Public Virus Scare Life Home	**Data Infrastructure** Sustain Share Innovation Open People Manage
	Lack & Skills	Infrastructure & Data	Fear	Infrastructure & Data
LONDON	Work Anger Business One **Money** Sadness	Cities **Data** Joy **Infrastructure** Want	**Fear** People Public Government Think Time Start Sadness	**Infrastructure** Network Power **Personal Data** Want
	Anger & Money	Infrastructure & Data	Fear	Infrastructure & Data
MILAN	Anger **Society** Care People Change Milan	Good **Money** Work Gratitude Want Love Like Joy	**Fear**- Person- Public- Stop- Work	Care Love People Power Think Sustain Joy **Share Knowledge**
	Society	Money	Ability	Society
MADRID	Anger **Knowledge** **Learn Lack** Difficulty Want Care	Care **Data** Desire Network Want	Fear- **Think**- Sadness- Job- Time One- Stop	Share Best Think **Sustain** Want Safe Calmness
	Lack & Skills	Personal Data	Fear	Society

can lead citizens to conceive smart technologies as a "luxury", or a means to enrich the powerful men.

The rage against technology expressed by the Italian citizens is related to the distrust toward society and public management of technologies and the non-acceptance of changes (Anger Care Public People Change Milan). Resistance to technology and the inability to accept new technologies (and the modification they bring in users' lives) are among the most assessed barriers to technology acceptance (Davis, 1989; Bhattacherjee et al., 2007). In previous studies, resistance towards technology is considered a key determinant of technology anxiety. Moreover, it can predict potential users' perception and behaviour (Lytras et al., 2021) and discard technology.

Lastly, the co-occurrence of words such as "fear" and "personal data" in Berliners' tweets seems to reveal a lack of trust in the transparency of data collection. Thus, it can be noticed that privacy and security issues, key challenges in the implementation of smart cities applications (Zhang et al., 2017), are the main concerns for Berliners' tweets in the sample.

In the pre-Covid period, the positive attitude toward the technology of Londoners and Dubliners is characterized by trust in the structural adequacy of technological infrastructure. Before the diffusion of Coronavirus, Londoners in the sample show a general satisfaction toward the technological architecture of their city and a positive mindset toward the use of data, seen as an opportunity for sharing and help (Cities Infrastructure personal Data Help Joy Want). Dubliners seem to consider technology as a means to improve cities, pursue innovative solutions and enhance well-being by creating a system and integrated architecture based on multiple touchpoints and devices, as shown by the co-occurrence of words such as "Future", "Internet of Things", "Manage", "Solution" (New Data Infrastructure Future Citizen Collaboration Iot Manage Solutions).

The positive attitude toward technology in Berliner's tweets before the advent of Covid-19 is not related to the adequacy of the technological infrastructure itself (characterized by a negative sentiment) but to users' trust in the ability of citizens to build a network of connections to create a better future through technology-mediated interaction based on sharing and mutual support (Future Build Citizen Sustain Connect Together Share).

The positive mentions of technology in the tweets posted by citizens from Madrid occur in topics related to general satisfaction and trust toward the use of personal data, seen as an opportunity for innovation rather than as a threat to personal privacy (Care Data Desire Network Innovation Want). In contrast, in the tweets posted by citizens from Milan, the positive mentions refer to satisfaction in using technology for work and personal life (Good Work Gratitude Want Love Like Joy).

Table 4 reports the key findings obtained from the analysis of tweets published before the advent of Covid-19.

4.1.2. The post-covid period

In the post-Covid period, the negative sentiment and anger toward technology expressed in the tweets by citizens from Dublin, London, Madrid, and Milan turn into fear.

In detail, Dubliners' tweets reveal the co-occurrence of topics such as "fear", "life", "home", "office", by showing a negative opinion of the new technologies imposed by the pandemic and the potential inability to accept the changes that Covid-19 brought into daily lives, work, and personal spaces.

The anxiety toward the technology of Londoners turns into a "collective" fear toward the public use of the technologies required to

Table 4
A comparison of citizens sentiment toward technology before Covid-19.

	Cities				
	Berlin	Dublin	London	Madrid	Milan
Negative Sentiment	Fear Privacy and security risks	Anger Inability to use technology	Anger Economic unbalances in the use of technology	Anger Lack of self-confidence	Anger Resistance to technology
Positive Sentiment	Trust in technology-mediated interactions	Structural adequacy of technological infrastructure	Structural adequacy of technological infrastructure	Trust toward the use of personal data	Effectiveness of technology for personal life and success

manage the pandemic (Fear People Public Government Think Time Start Sadness). The unsatisfaction toward both the individual and collective use of technology does not reveal the lack of trust in technology per se (the tools to employ new technological solutions). Still, it shows mistrust in policymakers (people who apply and support citizens in using technologies). The fear toward the technology of citizens from Madrid (Fear Think Sadness Job Time One Stop) is related to the individual dimension of isolation (“stop”, “one”) and of withdrawal into oneself (sadness and worry about time). It can be hypothesized that, as Covid-19 spreads, the general technology anxiety can be transformed into individual fear since social distancing makes people feel more and more isolated. The lack of sense of belonging toward the city and its managers confirms the existence of a misbelief of citizens in smart cities as a social and economic phenomenon (Simonofski et al., 2019; Visvizi & Lytras, 2019; Lytras, Visvizi, & Sarirete, 2019).

In the tweets of citizens from Milan, the fear toward technology is related to the lack of self-confidence in personal ability to use technology (Fear Person Inability One Stop). It can be noticed that the citizens’ technology anxiety shifts from a generic-collective dimension of dissatisfaction (before Covid-19) to individual fear (after Covid-19). In contrast, Londoners’ anxiety translates into a collective fear after the advent of the pandemic. In the first case, the increase of social distancing and the fear of contagion foster the isolation of citizens; in the second case, the perception of inadequacy and the sense of helplessness leads citizens to transfer their anxiety to society.

On the contrary, in Berliners’ tweets, the fear toward technology is transformed into anger, and the distrust is turned into suspicion toward government and the absence of technological support to citizens. In addition, the unsatisfaction toward the degree of democracy in the process of digitalization can be observed in the co-occurrence of words like “power”, “interest”, “support”, which can be considered as signals of a top-down power administration and of an incapability to align with citizens’ needs (Anger Everyone Power Government Data Interest Support Citizen Listen).

In the post-Covid period, the positive sentiment expressed by Twitter from the five cities shifts from an individual dimension to a collective and social dimension.

Dubliners express a positive sentiment toward technology that translates into an increased openness to data use by confirming the general trust in the technological infrastructure of the city for the development of innovation (Data Infrastructure Sustain Share Innovation Open People Manage). It can be noticed that after the advent of Covid-19, the confidence towards technology is boosted towards the enlargement of trust to a more “collective” sphere in which the human intervention of people that share their contribution is considered as a lever to foster the proposition of innovative solutions and to support the management of health emergency.

In Berliners’ tweets, the positive sentiment toward a collaborative approach to the use of technology (revealed in the pre-Covid era) is confirmed after the advent of the pandemic and strengthened through the increase in the sense of belonging to the community. Furthermore, the co-occurrence of words such as “partner”, “system”, “sustain” can be considered as a signal of the confidence of citizens’ ability to collaborate for the creation of a technological system activated by “people” as a real solution to compensate the lack of governmental support in the use of technology (Community Desire Sustain Want Partner Team System).

In the tweets of citizens from Madrid in the post-Covid period, the positive sentiment toward using technology is associated with words like “share” and “sustain”. Therefore, it can be assumed that after the advent of the pandemic, collaboration and sharing are intended as valuable means to increase collective well-being and mutual support (Share- Best- Think- Sustain Want- Safe- Calmness) and to control the negative impact of the emergency by avoiding panic (calmness).

In the tweets published by citizens from Milan, the optimistic attitude to technology is associated with trust in people’s use of personal data (Care Love People Power Think Sustain Joy Share knowledge) to increase knowledge and improve the sense of control over the emergency.

In the post- Covid period, the trust in data expressed in Londoners’ tweets is associated with a positive attitude toward the issue of privacy, which reveals that potentially the twitters do not worry about data manipulation (Infrastructure Network Personal Data Privacy Want).

In short, as Table 5 shows, the mentions of technology anxiety in Dubliners’ tweets reveal the heightening of the difficulties in the use of smart technologies, determined by the dramatic redefinition of daily lives that occurred after the diffusion of Coronavirus. However, despite the lack of self-confidence in using technologies, citizens show a positive digital attitude, characterized by a great sense of belonging to the community and a high degree of trust in the opportunities offered from shared use of smart tools.

The degree of technology anxiety of Berliners discloses a coping behaviour in the acceptance of the opportunities offered from a collaborative and bottom-up approach to smart technologies (before and during the pandemic), associated with the unsatisfaction toward the ability of government and policymakers in the management of technologies (emphasized after the spread of Covid-19).

Londoners show general compliance toward adopting a digital mindset and a high degree of trust in the potential of data and the appropriateness of the technologies employed in the city. This agreement toward the technological dimension is associated with a high degree of anxiety toward the adoption of technology for personal success and toward the improper management and support of the government in the use of technology.

Citizens of Madrid show a lack of confidence in their digital skills, and their attitude toward technology seems to worsen after the spread of Covid-19. However, these negative features are balanced with a high degree of trust in data sharing and people’s collaboration to limit the threats of the pandemic. The tweeters from Milan in the sample show a tendency to resist change before the advent of the pandemic. Then, after the spread of the Coronavirus, their degree of technology acceptance is reduced further. The uncertainty and anxiety related to technological dimensions are associated with a general positive mindset toward the use of data and toward collaboration between people to manage the negative effects of the pandemic.

4.2. Changes in technology anxiety before and after Covid-19

To assess if the trends in citizens’ sentiment identified above can predict changes in their attitude toward the technologies after the advent of the pandemic, Table 6 identifies the predictive performance of

Table 5
A comparison of citizens sentiment toward technology after Covid-19.

	Cities				
	Berlin	**Dublin**	**London**	**Madrid**	**Milan**
Negative Sentiment	Fear	Fear	Fear	Fear	Fear
	Mistrust in government and power imbalances in technology use	Inability to accept the changes dictated by the Pandemic	Mistrust in policy-makers	Isolation and withdrawal	Lack of self-confidence
	Collective dimension	Individual dimension	Collective dimension	Individual dimension	
Positive Sentiment	Collaborative approach and trust in people's sharing	Trust in data	Trust in data use and reduction of privacy concerns	Collaboration and sharing for mutual support	Trust in people and use of personal data
	From individual to collective dimension				

Table 6
Findings for RQ2: regression analysis.

Technology Anxiety Accuracy = 0.752	
Indicators	Coefficient β
LACK	−0.180*
INFRASTRUCTURE	−0.344*
MONEY	0.542***
PERSONAL DATA	−2.080*
SELF-CONFIDENCE	−0.413***
MISTAKE	−0.430*
ABILITY	−2.840***
SKILLS	0.029***
FEAR	−0.026*
ANGER	0.372**
DIFFICULTY	−0.724*

Note: ***$p < 0.001$. **$p < 0.01$. *$p < 0.05$.

the most recurring topics of technology anxiety (see column 1), taken as independent

variables, to classify sentiment after and before the Covid-19.

In detail, the first column of the Table reports the value of prediction accuracy (0.752), a performance measurement that specifies the ratio of correctly classified observations in the dataset. For example, a value of 0.752 shows that the proportion of correct predictions exceeds over total predictions in the association between the different indicators (independent variables) and the tweets in the pre-Covid period or post-Covid period (a dichotomous variable that ranges from 0 to 1).

In the second column, the coefficients from the logistic regression model predicting the dependent variable from the independent variables are provided in log-odds units. The coefficients (β) reveal the positive or negative incidence (proportionality) of the independent variables (anxiety indicators) on the dependent variables (period): a positive coefficient means that the attribute affects the pre-Covid sentiment, a negative coefficient means that the attribute affects post-Covid sentiment. A positive β shows the log-odds probability (incidence) of the occurrence of the given attribute in the pre-Covid period and a decreasing probability for the occurrence in the post-Covid period.

Moreover, p-values are reported to evaluate the degree of interest (significance) of the coefficients. The different values of significance are sub-divided into three classes: $p < 0.001$; $p < 0.01$; $p < 0.05$. As Table 6 shows, all the variables are significant.

The topics with the most positive and statistically significant log-odds coefficients are "money", and "anger". For every unit increase in their mentions, the log-odds probability of being cited in the pre-Covid period increases (the probability of being cited in the post-Covid period decreases) respectively by 54% and 37%. As discussed in paragraph 4.1, money and the concerns about the economic exploitation of new technologies are the most recurring topics in pre-Covid sentiment, which "disappears" after the advent of the pandemic that determines a shift of the focus to psychological and social concerns (fear, mistrust, isolation). Moreover, anger is a common negative sentiment that expresses a high degree of technology anxiety before the spread of Coronavirus in 4 out of the 5 cities (Dublin, London, Madrid, and Milan). The perceived lack of digital skills and the inability to use technologies has a strong significance (0.0) but a low coefficient, which shows a low probability of being cited in the pre-Covid period.

The topics with the most negative log-odds coefficients are "ability", "difficulty", and "personal data". For every unit increase in their mentions, the log-odds probability of being cited in the post-Covid period increases (whereas the probability of being cited in the pre-Covid period decreases) more than 70%. Ability and difficulty can be considered valid indicators of post-Covid sentiment. One of the key concerns of citizens in Dublin and Madrid is the lack of confidence in their digital abilities that reveals several difficulties in using new technologies. What is more, personal data is a commonly cited issue in the post-Covid period. It is related mainly to adopting a positive mindset toward digital culture (especially in Madrid, London, and Dublin).

Moreover, "lack", "self-confidence", "mistake", "fear", and "infrastructure" show lower β coefficients. For every unit increase in their mentions, the probability of being cited in tweets of the post-Covid period increases by around 18% and 40%. The motivation of the low coefficients can be found in the presence of these topics also in the pre-Covid period. Therefore, in the research sample, there is not a unique trend related to the perception of ability and self-confidence in the use of technology in each period. In one city, the issue is an indicator of post-Covid (Milan). In contrast, in two cities, it is an indicator of the technology anxiety before the diffusion of Coronavirus (Dublin and Madrid). At the same time, cities infrastructure is a commonly mentioned topic, which is debated both before and after the pandemic. For this reason, the low significance associated with its coefficient can be explained through the presence of this issue in the two times periods, which determines the almost total independence from the dependent variable (period).

5. Discussion: identifying the determinants of technology anxiety

The analysis of the public sentiment of citizens from the five cities investigated permits the identification of variations and unanticipated shades of meaning in the phenomenon of technology anxiety, which can reframe the key dimensions of the construct identified in extant research. Berliners' anxiety toward technology is determined mostly by an unsatisfaction toward government's management of technology and power distribution (cultural gap), balanced with a great sense of belonging to the community (social dimension) and a high degree of trust in the bottom-up use of technology.

Dubliners' resistance to technology is caused mainly by the fear deriving from a lack of self-confidence in using technologies and adapting rapidly to new technology (psychological factors). This psychological gap is compensated with a great sense of belonging to the community and a positive attitude toward a shared use of smart tools (social trust).

The key obstacles in using technology for Londoners are related to the mistrust in the economic exploitation of smart technology and the perceived uselessness of smart technologies for personal achievement (psychological inadequacy and low utilitarianism). However, psychological resistance is associated with a positive attitude toward the shared use of data (digital culture).

The anxiety toward technology perceived by the citizens of Madrid stems from a lack of self-confidence that, after the diffusion of the pandemic, turns into fear (psychological factors). This psychological inadequacy to adapt to new technologies is compensated with a general trust in data sharing and collaboration to manage the negative effects of Covid-19 (social trust).

Citizens from Milan show high resistance to change due to the perceived inability to use technology (individual and psychological level) and distrust in public management (cultural and context-dependent level). As in the other cities, there is a high degree of social acceptance of technologies and the general trust in people's use of technology through collaboration (social trust).

The different degrees of compliance toward technology and the different obstacles that prevent the full acceptance of technology revealed in the analysis are related in some tweets to social motivations, in others to psychological, cultural, or economic motivations. Thus, the different compliant and non-compliant behaviours detected in the sample of tweets can shed light on the varied spheres involved in the complex building of technology anxiety, which includes rational, cognitive, and psychological processes and can be affected by social, contextual, and cultural influence.

Starting from the commonalities and the discrepancies in the sentiment of citizens and, consequently, in their compliant and non-compliant behaviours toward technology, four dimensions that can foster the development of the multi-level process of technology anxiety can be identified: 1) utilitarian; 2) psychological; 3) social; 4) cultural. As Table 7 shows, the four dimensions are obtained from the indicators of anxiety derived from literature, confirmed and enriched through the results, and reframed and re-elaborated to identify the key determinants of technology anxiety (See Table 7).

The identification of four interdependent dimensions can enable the categorization of some determinants of technology anxiety. These dimensions can be synthesized in a framework that introduces an integrated and holistic understanding of users' perceptions about technology in smart cities by conceptualizing the multi-levelled psychological and social beliefs, cultural habits, and rational factors engaged in the complex acceptance of technologies and technological changes. The different determinants of technology anxiety, depicted in Fig. 3, are discussed in the following sub-paragraphs.

Table 7
The identification of the determinants of technology anxiety in 5 smart cities in Covid-era.

Indicators confirmed	Related topics emerged from the analysis	Macro- areas/ determinants of technology anxiety
Money	Power; Interest; Business; Work	Utilitarian Dimension
Lack	Abilities; Confidence; Knowledge; Learn	Psychological Dimension
Ability	Fear; Inability; Person; Stop; Skills; Confidence	
Fear	Sadness; One; Time; Stop; Life; Home; Office	
Difficulty	Learn; Knowledge	
Personal Data	Privacy Want	
Infrastructure	New; Data; Collaboration; Network Community; Sustain; Sharing; Internet of Things; Manage; Solutions	Social Dimension
Data	System; Open; People; Build; Future; Innovation	
Anger Meuter et al. (2003)	Government; Public; Support; Citizen Listen; Change	Cultural Dimension

5.1. Utilitarian dimension

The utilitarian dimension is referred to the rational and cognitive evaluations that lead citizens to assess technology based on the individual and social benefits provided.

In the results obtained from tweet analysis, three sub-dimensions can be identified: 1) perceived social usefulness; 2) ability of government to allocate resources and distribute technological power; 3) perceived personal fulfilment.

The first sub-dimension concerns the worries about the economic exploitation of technology implementation in smart cities and about the management of profit and the allocation of resources on the part of the government, associated with a low degree of perceived social usefulness. Citizens' evaluation of the appropriateness of the money spent on smart city services influences the perception of smart technologies as useful means for society. If people believe that smart technologies are a luxury and do not compose the basic infrastructure of a city, they will consider technologies useless, and this will increase their resistance to use them. Users who perceive advanced information systems as levers for inclusive and sustainable socio-economic growth will be more predisposed to adopt technologies and to accept the changes brought by their adoption.

The second sub-dimension refers to the appropriateness of governance and technology and human capital, as one of the major contributors to citizens' participation and smart city development. Different governance models for the distribution of technological power and different kinds of support to the access and use of technology can enable a different degree of technology acceptance in citizens' perception. In this sense, Helsinki smart city is one of the European best practices in developing a bottom-up approach (Anttiroiko, 2016) based on the resolution of urban problems through triple helix collaboration (Hämäläinen, 2020). Through a series of smart projects and innovation platforms (such as Forum Virium Helsinki), citizens are engaged in the co-design of the smart city as the most precious resource and the beneficial owners of the benefits generated within the city. Moreover, non-profit associations, local businesses, citizens, and students are involved in the co-creation of new ideas and innovative services (such as healthy neighbourhoods, mobile services tests, waste collection systems) through innovation communities, collaborative urban design, joint investments, living labs, open data.

Lastly, the utilitarian dimension can involve the creation of obstacles or enablers of technology acceptance. In the sample of tweets, people

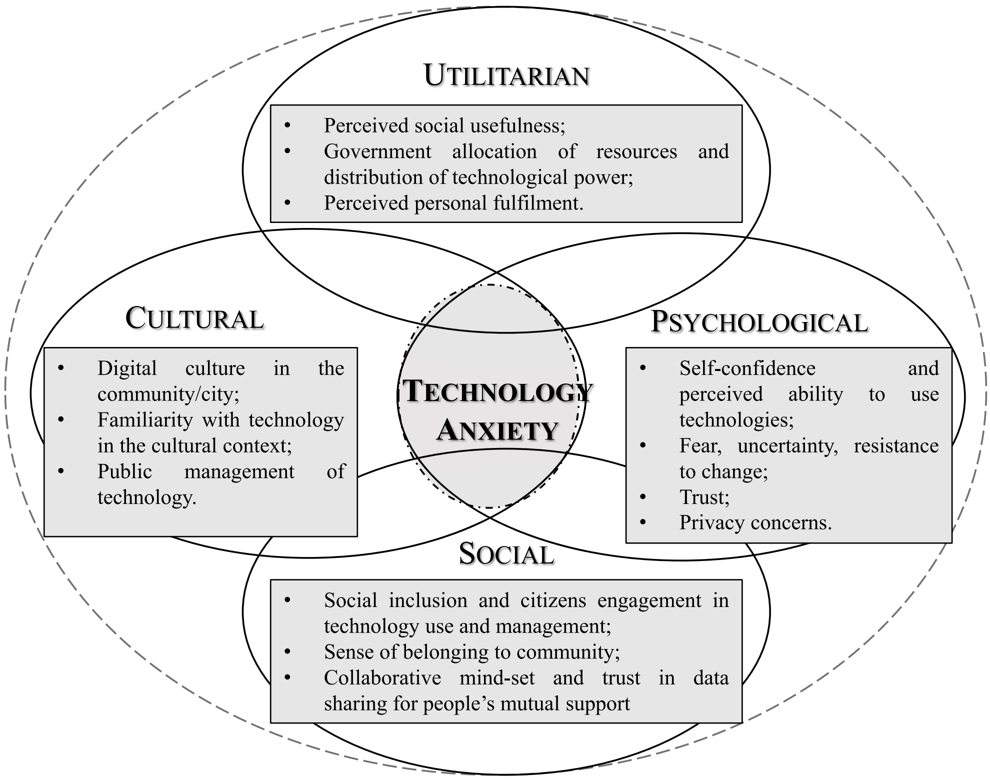


Fig. 3. A multi-levelled framework for the determinants of technology anxiety.

with a high degree of dissatisfaction toward the use of technology for the fulfillment of personal success can develop more probably a negative sentiment toward technology. Thus, users with low anxiety perceive higher facilitating conditions than users with a high level of anxiety.

5.2. Psychological dimension

As Fig. 3 shows, the findings of the empirical research reveal that the psychological factors that can prevent a full acceptance of new technologies are: 1) the lack of self-confidence and the perception of inability to use technologies; 2) fear and uncertainty, which determine resistance to change; 3) the mistrust in technology, in government's and people's management of technology; 4) the privacy concerns. Psychological factors can motivate users to adopt smart-cities services and help individuals achieve their personal and professional tasks (Macke et al., 2019). The psychological impact of technology is widely debated in the literature. For example, perceived self-efficacy, self-confidence, and self-esteem are considered threatening factors for developing technology anxiety (Bandura, 1986) and the decrease of the sense of control over daily activities. Therefore, reducing anxiety can increase the sense of control and make the events more predictable by decreasing the feeling of risk. One of the effective strategies to reduce citizens' perception of the inability to use technology is to increase digital skills and culture. For this reason, the development of digital competencies (for children, practitioners, urban managers, and citizens as a whole) has been settled as one of the priorities of the European Digital Agenda 2020. Digital citizenship, as the exertion of active engagement in the development of cities and communities, has been promoted over the last years in international smart cities to address the lack of digital skills in students, citizens, and public administration workers. For instance, UK Government is encouraging the implementation of digital citizenship as a mandatory subject in schools. Similarly, Common sense, a British non-profit organization, is devoted to providing services for the improvement of kids' and families' education by offering them trustworthy information and the right competencies and attitude to thrive in the digital era. Fear and uncertainty are other recognized enabling factors of technology anxiety. If anxiety is related to the lack of control, fear stems from an emotional state of fright that leads users to perceive a threat in their lives.

Trust is one of the most effective sensations to reduce uncertainty and to generate a sense of safety related to the use of technology (Lin, 2011). Users' and citizens' trust in technologies and service providers plays a crucial role in the intention to adopt the technology. Trust has a key role in reducing perceived risk, enhancing usage behavior, behavioural intention (Yoon, 2002), and perceiving the usefulness of technology (Ha & Stoel, 2009). In the sample of tweets, citizens do not show a lack of trust in technology per se but reveal a mistrust in policymakers' application of smart technologies and in governmental support to use technology (Hartanto & Siregar, 2021).

Lastly, researchers identified the security and privacy issues as the major challenges to adopting and accepting technology (Hancke et al., 2010). From the individual users' perspective, the use of smart technologies involves a series of concerns about privacy, security, and who has access to data collected by governments and companies (Weber, 2010) and in smart cities (Van Zoonen, 2016). Privacy is considered as one of the most common inhibitors of technology adoption (Venkatesh et al., 2003). It can be defined as the individual believes that make users sceptic about releasing their personal information to others (Xu & Gupta, 2009).

5.3. Social dimension

The social determinants of technology anxiety (the social features associated more frequently with negative sentiment toward technology in the tweet analysis) are: 1) social inclusion and citizens' engagement in technology use and management; 2) sense of belonging to a community; 3) adoption of a collaborative mindset based on the trust in data sharing and people's mutual support.

Technology anxiety in the tweets analyzed is associated with the development of social exclusion, which can stem from the lack of skills to use smart technology, the inability of the government to involve citizens in the use of technologies by removing the obstacles to access infrastructure. These findings reveal the need to understand the smart city as a social and political phenomenon (Visvizi & Lytras, 2018) and as a leading actor to build an inclusive society and boost participation. The digital divide and the gap in the technological skills of managers and citizens can be addressed through the engagement of stakeholders and a diffused decision-making (Nurmandi et al., 2017).

The sense of belonging to the community revealed in the tweets highlights the weight of social influence on technology anxiety. As confirmed in the literature, users with a high level of technology anxiety tend to be more influenced by the opinion of other people and by society (Yang & Forney, 2013). Extant research shows that a high level of technology anxiety is related to a lack of confidence; hence, users with a high level of anxiety rely more on family's and friend's beliefs and follow referent group norms to use technology (Kulvivat et al., 2009).

The degree of trust toward the community and enhancing the sense of belonging can be strengthened through social initiatives such as civic crowdfunding. For instance, in Milan, new spaces for collaboration and co-design have been created to reduce the gap between civil society and decision-making. The project started in 2020, involved non-profit organizations, citizens, and third sector organizations (social enterprises, associations, foundations, etc.) that proposed over one hundred projects. As a result, the municipality has selected the best twenty bottom-up projects to realize a series of smart activities for urban revitalization and technological accessibility by engaging users in the decision-making of the projects.

In all the cities included in the sample, the most common positive sentiment toward the use of technology is trust in technological infrastructure and data sharing, intended as useful means to increase collective well-being and mutual support and to control the negative impact of the emergency by avoiding panic. The sharing and the collection of big data in smart cities are viewed in the sample of tweets as a new method to enhance growth and address social issues. Data sharing can ensure the real-time collection of epidemiological data and can strengthen risk-assessment, decision-making processes, and the design of public policies (Allam & Jones, 2020). Moreover, the adoption of a collaborative mindset based on data can be fostered through the constant sharing of information, technical experiences, and knowledge between experts and civil society to involve citizens in the active use of technology and the proposition of innovative policies for the territory. Open data projects and hackathons seem to be useful practices to raise citizens' involvement in a better and more acknowledged use of technology and the co-development of innovative solutions. For instance, the open data hackathon at the municipality of Livorno held in 2018 aimed at increasing citizens' digital culture and simplifying the access and use of data (geographic, geo-referenced, or geo-referenced data) to make every actor understand how to extract relevant content from data. Then, after the diffusion of technological capabilities, the data analyzed was used to create cultural or environmental activities in the city or the territory by supporting mart actions or projects (e.g., the recovery-revitalization of underused or degraded areas).

5.4. Cultural dimension

The cultural determinants (obstacles or enablers) of technology anxiety identified in tweet analysis are: 1) digital culture in the community/city; 2) familiarity with technology in the cultural context; 3) public management of technology.

Developing a cohesive culture is considered in the literature as a critical lever for adequate exploitation of technologies and data analysis opportunities in companies, organizations, and cities. It has been demonstrated that the primary cause of failure in technology implementation is the absence of a totalizing digital culture rather than the structural characteristics of technology (LaValle et al., 2011; Ross et al., 2013). In the sample of tweets, a positive attitude to the use of data for cities growth and innovation has been revealed. A data-driven culture is defined in the literature (McAfee & Brynjolffson 2012) as an approach to decision-making based on the relevance of data (and of the insights extracted from it) as a strategic asset to undertake more effective decisions. Extant research shows that the enhancement of digital literacy (Axelsson et al., 2010; Wiig, 2016) can enable citizens' engagement in cities decision-making by implementing a series of digital strategies and smart projects that can create an ecosystem of citizen-centric services. For instance, the activity "Smart Polis2020", launched by the Puglia Region in 2019, aims at creating a new version of smart cities that involves citizens in the design and implementation of policies. Smart polis can be intended as a physical and geographical place built on a network of new technologies, but also as a relational space "delimited" by cultural, social, political, and economic connections which, if exploited appropriately, can permit users to co-create innovative services and satisfy individual and community's needs.

The general familiarity and unfamiliarity of citizens with technology and the potential adoption of a digital culture stem from the different management of cities realized in the different national contexts, in which government can adopt a top-down or bottom-up diffusion of technological tools and can prevent the spreading of digital skills with a low degree of support to the use of technology. The national culture and the political context can influence citizens' attitudes and behaviours toward technology and can prevent the acceptance of technological changes (Harris & Davison, 1999). Extant research shows that technology anxiety does not depend only on an individual's unfamiliarity with technology but also on situational and context-dependent factors that enrich users' experiences and perceptions of technology use.

As the findings of the tweet analysis reveal, government support and diffused decision-making can be associated with citizens' positive perceptions of technology. This result is confirmed by Ramanathan et al. (2014), who hypothesize that a higher level of government support can help the strengthening of usability and adoption. Different kinds of support are identified in the literature: financial, project, training, and regulatory approval (Lin & Ho, 2009). Other scholars analyze the relevance of citizens' engagement in the decision-making of cities and in the community's life as an enabler of technology acceptance in city space that must also be considered (Nurmandi et al., 2017). Citizen participation and engagement are crucial drivers of citizens' successful deployment of ICT (Olphert & Damodaran, 2007).

6. Theoretical and managerial implications

The key theoretical contribution of the study is the building of a framework that detects the main psychological, rational, social, and cultural determinants that can foster or prevent the acceptance of the changes forced by the pandemic, the adhesion to digitalization, and the transactional distance processes launched in the public sectors.

The recognition of the strategic drivers for optimal exploitation of technologies in managing health emergencies can enrich policymakers' and public managers' understanding of the assessment, forecasting, and management of crises and emerging events. The main managerial contribution of the study is the proposal of a tool to improve the decision-making process by detecting the criticalities in citizens' adoption of technology through a classification of the main factors that hinder or enable efficient use of technologies and redefine the daily lives of individuals and human-machine interactions. Some of the critical factors identified, such as the lack of self-confidence in digital skills or the perceived lack of governmental support in the use of technology, can help managers discover the strategic levers that can be employed to align with the needs and expectations of end-users.

The results of the empirical research reveal that individuals with a high level of technology anxiety are less disposed to make use of it (Meuter et al., 2003). Thus, exploring and detecting the degree of anxiety toward technology plays a vital role in successfully adopting smart services.

Moreover, shedding light on the most common topics shared on social media platforms related to Covid-19 and the management of public health emergencies can provide policymakers with relevant suggestions to challenge the negative implications of a pandemic, assess the needs of stakeholders, and address them appropriately (Abd-Alrazaq et al., 2020). Anxiety plays a key role in shaping behavioural responses to the public health emergency; hence, it is critical that decision-makers recognize the multiple individual psychological responses to the current crisis (Wahbeh et al., 2020).

The classification of the different emotional shades of public sentiment/technology anxiety can foster smart cities management. The rapid spread of Coronavirus and Covid-19 infections created a strong need for discovering efficient analytics methods for understanding the flow of information and the development of mass sentiment in pandemic scenarios. While numerous initiatives analyze healthcare, economic, and network data, there has been relatively little emphasis on analyzing the aggregate personal level and social media communications.

Sentiment analysis using social media data will thus provide valuable insights on attitudes, perceptions, and behaviors for critical decision-making for business and political leaders and societal representatives. As a global pandemic, Covid-19 is adversely affecting people and countries. Besides necessary healthcare and medical treatments, it is critical to protect people and societies from psychological shocks (e.g., distress, anxiety, fear, mental illness) (Hung et al., 2020). In this context, automated machine learning-driven sentiment analysis could help health professionals, policymakers, and state and federal governments to understand and identify rapidly changing psychological risks in the population. Identifying public sentiment can detect the strategies that can reduce people's uncertainty and detect the factors that can prevent engagement and compromise the diffused decision-making in the digital ecosystems (Samuel et al., 2020).

In the era of digitalization, the exploration of online activities is one of the most useful means to understand the motivation of real-life activities and behaviours. Consequently, to detect a possible response to public health crisis, the analysis of users' opinion on social media can provide policymakers with relevant insights on the people's reactions to the state of emergency (Ordun et al., 2020). In addition, it can offer an opportunity to communicate directly with public opinion. Monitoring users' activities on social media can permit organizations, public institutions, and companies to be more proactive, challenge the spread of fake news, and limit the propagation of the negative psychological effects of pandemics (Chakraborty et al., 2020).

7. Conclusions

The impact of Covid-19 on people's lives, organizational practices, urban policymaking, and decision-making entails the need to capture how individuals react to public health emergencies (and to the management of this emergency) and reveal their concerns. For this reason, this paper aims at investigating citizens' sentiment and concerns about the Coronavirus pandemic and at identifying the sources of these concerns by exploring tweet's posts to discover people's reactions to social issues.

The framework proposed helps enrich the debate on the determinants of technology anxiety and identifies the different criticalities that influence citizens' behavior and attitude concerning tools and instruments used to digitize the relationships between individuals and organizations.

The classification of some cultural, social, and psychological drivers can help urban policy-makers in the identification of the most proper strategies and practices to involve citizens in public decisions (Abbas et al., 2021), to enhance social inclusion, and to enrich their digital culture by removing in this way the barriers to the use of technology. Moreover, the four macro-dimensions detected in the framework can be generalized to smart cities contexts. They can be broadened to analyze the key levers to reduce the digital divide in smart communities (Li et al., 2019) and smart villages in which, according to extant research (Tran et al., 2017; Yu et al., 2017), there is the need to reveal some strategies to support underprivileged people or individuals that do not have the right skills to use technology. By clarifying the means to reduce technology anxiety, the study can suggest how to enhance citizens' perceived usefulness of technology to challenge pandemics and foster the restarting of the economy and social activities. Policy-makers should highlight the potential benefits of technology, such as improved efficiency and performance of healthcare, mobility, and public services in general. In the EU, as discussed above, several attempts are made to coordinate the policies on smart cities through a series of initiatives on sustainability and digital culture (Agenda 2020; SDGs, etc.); however, the power of decision remains at the city level, and this can prevent a full harmonization of the strategies across the different nations. The discussion of some international cities that can be considered best practices in implementing smart projects advances the first step for applying the framework to other urban contexts by confirming the generalizability of the four dimensions. In this way, it can be noticed that citizens' inclusion and digital literacy are relevant issues that do not apply only to urban contexts and should be addressed to solve societal, economic, technological, and political problems worldwide. Thus, a new mindset for education that goes beyond the urban context is spreading to pursue the objectives of technological access and digital literacy for children, students, teachers, policy-makers, practitioners, and managers to build a shared digital world (Johnson et al., 2021). The categorization of the main determinants of the technology anxiety developed after the advent of the pandemic can be intended as a starting point for further qualitative and quantitative research to explore the drivers of the change in citizen's sentiment before and after the spread of Covid-19. First, a mixed-method approach can enrich and extend the framework proposed in the study through observations and the administration of semi-structured interviews to a sample of citizens to identify a most detailed classification of the key indicators of technology anxiety. Then, by transforming the indicators into items, a measurement scale of technology anxiety can be tested and validated through quantitative analysis based on regression and structural equation modelling. A limitation of the study can be found in the discrepancy between online behaviour and offline behaviour and the difficulty in exploring psychological characteristics through social media analysis. However, it is acknowledged that users currently perceive their online profiles as an extension of the self rather than a separate entity, revealing their real psychological features. Moreover, the technique employed (and actual data mining and machine learning techniques) can ensure a great level of accuracy to predict characteristics based on online data (Gouda & Hasan, 2019).

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